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Owen Powell

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PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de Universiteit van Tilburg op gezag van de rector magnificus, prof. dr. Ph. Eijlander, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op woensdag 22 september 2010 om 10.15 uur door

OWEN RAYMOND POWELL

geboren op 1 juni 1980 te Victoria, Canada.

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OVERIGE LEDEN:	dr. P. Kujal prof. dr. W. Müller prof. dr. J. J. M. Potters prof. B. Ruffieux prof. J. R. Tyran

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I will begin by mentioning the committee members for the time and effort they have all put into scrutinizing my work and offering their feedback. I would like to thank Professors Ruffieux and Tyran who were able to travel from abroad to attend the defence ceremony. I am grateful to Jan Potters and Wieland Müller, who formed part of the inviting environment at Tilburg that helped spawn my interest in experimental economics. Praveen Kujal has become a close colleague in Madrid and has helped me hit the ground running over there. And finally, my advisor Charles Noussair who managed to not only help refine my thoughts and ideas on bubble markets, but also acted as an excellent mentor to the nuances of life in academia.

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I lived, worked and played with so many interesting people during my PhD that the memories will last a lifetime. I will remember all of my housemates, my classmates and our discussions on the morning train to Utrecht, the fun to be had learning Dutch, and the pleasant ladies with whom I was able to share an office with. The friends who were there to help when needed, the ones who let me visit them in their homes. I will also always recall the many frisbee games, running in the forest and driving to football matches in small villages on Sundays. Picnics in the park, the Carnaval and parades, Kandinsky, the LAN parties, and riding a bicycle home late in the evening will also not be forgotten. The places I have been able to visit so far: from Morocco to the Ukraine and the many, many places in between, they have opened my eyes to the world. Sleeping on a Dutch beach, biking in the French Alps, a Belgian wedding, climbing in Spain, a traffic jam on the way to Berlin, etc.

The list is not meant to be exhaustive - it does go on, and on, and on. My only hope is to let all of those that I have had the pleasure of meeting over the years know that I remember the moments we shared and appreciate our time together. I am a better person for it, and thank you for that.

I left Canada 5 years ago on an airplane with only the vaguest idea of going to Europe to do an economics PhD. Then I took an experimental economics class, and the rest is essentially what you see here. Obviously many influences played a role in getting me on that airplane, but 3 in particular stand out as helping me challenge myself and seek out interesting questions. The first is my father, who, when I was a young child, amused me to no end by giving me math problems involving bricks and wheelbarrows that I would contemplate in my mind as I lay in the bath. The second is my high school math teacher, Mr. Zak, who would post math problems on his door for students to solve for fun. I have fond memories of trying to calculate the number of sheets of paper that fit into a recycling bin. I have a vague feeling that not many students ever attempted, let alone read, the problems he would post, but to me they were often the highlight of my week. The third is an economics teacher I had in Canada, Professor Ferguson, who managed to fascinate me so much with a lecture on Leontief Input-Output models that I devoted the next 8 years of my life to learning about and studying economics.

And finally, as is usually the case in situations such as these, my family - parents, brothers and family pets - have provided an incredibly supporting environment that has allowed me to explore the world, comfortable in the knowledge that there is always a white house full of warm arms (and paws) waiting for me on Barrie Road.

The night is late and the proverbial light of my mind grows dim, but I cannot end in good conscience without specifically mentioning the three wonderful girls I shared so much with in Tilburg: to Heejung, Anna and Roberta - 10/10.

Owen Powell
Victoria, August 2010

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CHAPTER 1

INTRODUCTION

1.1 When Markets Fail

Markets play at least three important roles in the economy. First, they allow for exchange. Goods and services are able to be re-allocated to those who value them most highly. Second, markets allow for the pooling and reduction of risk. Proper diversification can reduce the amount of risk faced by individuals. Third, markets can aggregate information.

It is this third function of markets that is the study of this thesis. Through their transaction prices, markets have the potential to aggregate diverse information and provide signals to agents about the relative, *fundamental*, value of different goods and services. The task of evaluating the relative values of the many goods produced by society can seem to be a formidable task, yet competitive markets can (at least in theory) solve this problem, in an inadvertent form of crowd-sourcing. This process is referred to as *price discovery*. Relatively high prices, for example, can signal that a good is very valuable to society - agents then have an incentive to increase their supply (production) of that good, while at the same time reduce their demand for it (as consumption and/or as an input into production). In this way prices can provide a guide to society about how to consume and allocate productive resources. When price discovery has taken place, markets are said to be *efficient*.

The problem, however, is that there is no guarantee that market prices *will* exactly aggregate all individual preferences so that relative prices correctly reflect fundamentals. In fact, there is no guarantee that they will do so even approximately correctly. When prices differ from fundamentals there is said to be *mispricing* in the market. One such pattern in which prices can deviate from fundamentals is a *bubble*. As Siegel (2003) puts it, "[t]he word bubble conjures up the image of an object growing steadily until it finally pops". In asset market terms, the object that is growing is prices relative to fundamentals. A bubble is a period of persistently growing over-pricing, culminating in a sharp drop, or *crash*, in prices towards fundamentals. If fundamentals are relatively stable over this period, then prices tend to grow and grow until one day they crash spectacularly.

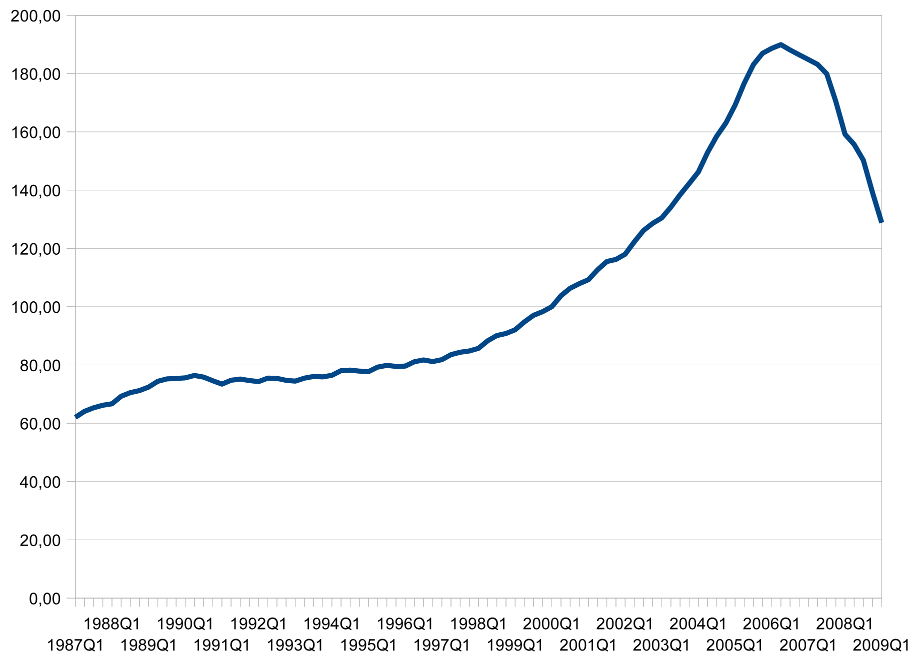
These events often leave chaos in their wake. Those caught unaware by the crash in prices experience significant losses that often lead to cascading effects in other parts of the economy. The direct cost of a bubble is the over-investment that results from the temporary over-pricing of the asset. The indirect costs of a bubble are the consequences of the typically large and rapid redistributions of wealth that occur when prices crash at the end of the bubble. These large fluctuations in wealth can lead to social disruption and have spillover effects on the rest of the economy.

1.2 Does It Happen Often?

But how pervasive are these bubbles? Do they only occur in specific types of markets, or during specific parts of history? Or can they potentially occur in all types of asset markets?

Consider a recent example of such price behavior. From the mid 1990s onwards, U.S. housing prices grew at an abnormally rapid pace for more than decade. Following the peak in their levels near the beginning of 2007, prices fell rather abruptly. By late 2007, public officials were taking note and expressing their concern. Henry Paulson, the U.S. Treasury Secretary, opined that he saw "[the housing decline] as the most significant current risk to our economy" (U.S. Office of the Treasury (2007)). Nevertheless, he put forward an optimistic view, stating that "[e]ven so, I believe we have a healthy, diversified economy that will continue to grow".

Figure 1.1: U.S. Housing Prices, 1987 - 2009



Notes: The figure shows the Case-Schiller U.S. national housing price index for 1987Q1 to 2009Q1. Source: Standard & Poor's.

By the end of 2008, the Case-Schiller Housing index (see Figure 1.1), a leading indicator of housing value, had decreased by 30%, returning to levels last seen in 2002. These price movements were far different from historical trends for the index. The previously high prices had led to over-investment in U.S. housing, both by consumers and builders. This meant that after the crash, the U.S. was left with a glut of excess housing supply, and millions of American homeowners were forced to either foreclose on their mortgage or go through costly mortgage re-financing. Financial companies with large amounts of mortgage loans faced severe losses. For example, the five largest U.S. investment banks at the time were either taken over (Bear Stearns and Merrill Lynch), bailed-out (Goldman Sachs and Morgan Stanley), or went bankrupt (Lehman Brothers). The failure of these institutions caused panic in other financial sectors and precipitated government intervention the world over (see, for example, Demyanyk and Van Hemert (2009) and Mayer et al. (2009)). The free-fall in housing prices became blamed by many for triggering a worldwide global recession whose effects still linger in various economies to this day. Two years later the U.S. "housing bubble" would be blamed in part for the "worst financial crisis since the Great Depression" (Reuters (2009)). The possibility raised by this very salient example is that market prices may become de-coupled from what is considered to be their true values, and that this de-coupling has real negative effects on the economy that can spread beyond its origins.

The example also makes it clear that price bubbles are a present concern in today's highly-integrated world. It has, however, long been argued that deviations of prices from values are commonplace and substantial, and that asset prices readily become decoupled from fundamental values (see Shiller (2003) for a review) and form market bubbles (Shiller (1981); Froot and Obstfeld (1991)). From a theoretical point of view, booms and crashes have been modeled both as originating from the presence of irrational trader types such as feedback traders (see for example De Long et al. (1990)) or overconfident traders (Scheinkman and Xiong (2003)) as well as rational phenomena (Tirole (1982); Abreu and Brunnermeier (2003)). Most disconcertedly, bubbles have been shown to arise even when the fundamental value of the asset is known to all market participants. Camerer (1989) refers to this as a rational growing bubble: "The hallmark of the rational growing bubble is that traders realize prices are much higher than intrinsic values, but they buy assets anyway, expecting prices to go even higher". Thus there appear to be few, if any, *apriori* limitations on when bubbles may arise.

On the other hand, the suggestion that price bubbles and crashes are pervasive is unappealing to many economists because such mispricing is at odds with classical economic and financial theory. Thus, there is an ongoing debate about whether asset prices have a tendency to deviate from fundamentals as a matter of course, or whether deviations from fundamentals are a rare, unbiased, or rather inconsequential phenomenon (Fama (1998); Malkiel (2003)).

Table 1.1 contains a selection of some of the more well-known market episodes which have displayed behavior consistent with a bubble[1]. The list goes back to the early 1600's, and spans the range of highly sophisticated technology and banking sectors to basic commodities, suggesting that bubbles can occur in all types of circumstances.

Whether or not an episode qualifies as a bubble or not is the subject of considerable debate. For example, Temin and Voth (2004) have argued that during the South Sea episode at least one major investor was aware that the market was in a speculative bubble. On the other hand, Pástor and Veronesi (2006)

[1] Kindleberger and Aliber (2005) provides an exhaustive discussion of many more examples.

Table 1.1: Ten Potential Bubbles

Episode	Bubble	Crash
1634-1637, Dutch tulips[a]	+5000%	-90%
1718-1720, Mississippi bubble[a]	+2000%	-60%
1719-1720, South Sea company[b]	+843%	-88%
1842-1849, Railway Mania[c]	+100%	-60%
1928-1932, U.S. stocks[c]	+100%	-60%
1969-1970, Australian mining companies[c]	+2800%	-100%
1986-1991, Japanese real estate and stocks[d]	+110%	-63%
1998-2001, U.S. internet companies[e]	+150%	-78%
2004-2008, Uranium[f]	+650%	-60%
1996-2009, U.S. real estate[g]	+120%	-40%

[a] Garber (2001). [b] Temin and Voth (2004). [c] Simon (2003). [d] Siebert (1999).
[e] Google, Inc. [f] http://www.uranium.info. [g] Standard & Poor's, Inc.

find that the runup and decline in the NASDAQ index was not indicative of a bubble. French and Poterba (1991) argue that the Japanese stock market bubble of the late 1980's cannot be explained by changes in fundamentals. Garber (2001) argues that the Dutch tulip mania, the Mississippi bubble, and the South Sea company episodes were not bubbles. But even with caveats such as these, it is reasonable to conclude that it is impossible to rule out the existence of bubbles in a wide variety of markets.

1.3 How Do Bubbles Work?

The next question worth asking is whether such events can be controlled, predicted and/or prevented. In order to answer these questions, it helps to outline the sequence of events that underlie a bubble. Kindleberger and Aliber (2005) use an exhaustive historical record to piece together clues about how bubbles manifest themselves, surge, and eventually reach a tipping point that leads to their ultimate demise.

The typical story goes something like the following. A bubble is brought into being by some positive exogenous shock that increases the value of an asset sharply. These shocks may be attributed to the beginning or ending of conflicts, technological innovation, or changes in government policy. This initial shift in fundamentals has a subtle effect on investors - they bear witness to some investors making large portfolio gains from the asset over a short time period. Observing these gains, more and more investors start believing that short-term capital gains may be realized from investing in this asset, or even that the trend in fundamentals has shifted. This sparks the flame that eventually leads to a wildfire in positive sentiment regarding the asset, until a white-hot mania has swept over the market.

While the mania spreads, pushing the asset's price to ever-higher levels, a counter-acting force gathers strength. Investors transfer more and more of their wealth into the bubbled asset, making it harder and harder to finance new holdings of the asset. Credit slowly dries up, making each new investment in the asset harder to make.

Eventually, there comes a point where the forces of scarce credit and rational beliefs about the fundamental value of the asset over-power the frenzy of short-term capital gains expectations. At this point, the brief "calm" before the storm, the market reaches its peak. Then cool heads, who realize roughly how over-priced the asset is, and thus how far it must eventually crash, lead a rush to get out of the asset. So much credit is tied up in the asset that it makes it difficult to find outside buyers who might think of reversing the trend.

The scary thing about a bubble is how quickly prices can fall at the end. This "panic" in one asset class becomes a very noticeable, albeit by itself not terribly important, event. The problem arises when panic about the direct repurcussions of the crash, which can have a significant effect on the portfolios of market participants, can have spillover effects on the rest of the economy, so that doubt about the stability of the entire system is created.

Once things have progressed to the point of free-falling prices and dimishing portfolio values, one of the few policy options is direct intervention by some body - what Kindleberger and Aliber (2005) refer to as a *lender of last resort*. The role of the lender of last resort is to supply money to "otherwise previously solvent and well-capitalized firms" (p. 225). The most recent global recession, which included extensive government intervention to prop up or nationalize failing financial institutions in several countries, shows that this line of action is currently deemed a reasonable response to these types of crises.

There are, however, several difficulties with such an approach. The first is determining which firms are worthy of the lenders support. Which firms were "otherwise previously solvent and well-capitalized"? A fine line must be drawn between firms who had or had not made reasonable investments. Another complication is the point in time at which the lender should intervene. At which point do you increase credit to soften the landing of the bubble without running the risk of prolonging the boom phase of the cycle? Finally, how is credit supplied to ailing firms? Concerns about public control of private enterprises abound in these circumstances. When the lender of last resort chooses to become involved with private enterprises, it needs to have a coherent plan for both getting in and getting out of its position. The answers to these questions of who to provide credit to, at what time, and under which conditions is not immediately obvious.

In addition to handling the immediate crisis, another problem is the long-term effects of "rescuing" market participants who have suffered significant losses. The moral hazard created by such activity has the potential to worsen future speculative episodes. As the English philosopher Herbert Spencer wrote: "The ultimate result of shielding men from the effects of folly, is to fill the world with fools.". The danger is that saving those who speculated today will send a signal to investors that they will not end up bearing the entire risk of future speculative actions, making it more likely that bubbles will re-occur.

The other option is to take pre-emptive action to limit the size of bubbles. This includes deposit insurance and bank holidays, which are designed to shelter banks from experiencing runs on their deposits. Another option is releasing public announcements that warn of a bubble in progress. The hope is that such announcements will trigger a milder crash to fundamentals before the bubble has had a chance to reach its naturally occurring peak level. Other possibilities include speculation taxes (which make speculation less attractive) and clearinghouse certificates (which are a type of mutual insurance agreement between companies).

Gauging the effectiveness of these methods with a clear mind is not an easy task. Unfortunately, as the recent global downturn demonstrates, the onset of a crisis seems to spur the formation of all manners of opinions around the subject, opinions that may be too easily be influenced by present circumstances rather than objective evidence.

1.4 Observability

One difficulty with analysing bubbles and policies designed to limit their occurrence is that even with hindsight, it is hard to establish with certainty whether a bubble has occured or not. In order to establish that any kind of mispricing has occured in a market, it is necessary to know prices and fundamentals. Prices are usually not too difficult to observe, however fundamentals, even several years after the fact, may still remain unknown.

Consider the example given at the beginning of the chapter. U.S. housing prices peaked sometime in 2005 after several years of abnormal increases. This was followed by an on-going crash. Casual inspection of the price pattern suggests that a bubble might have occured, given that the the market had been operating efficiently in the 1990s and that this trend in fundamentals had continued into the next decade. Note, however, that whether or not the run-up and subsequent crash in prices was a bubble depends critically on what was occuring to fundamentals during that time, which is very difficult to determine.

This is the *observability* problem associated with trying to measure bubbles. Tests of fundamental pricing typically involve postulating a hypothesis about the fundamental value of an asset and measuring how well prices track fundamentals under the assumption that the hypothesis governing fundamentals is correct. Fama (1970) makes the point that these tests are in fact joint tests of price discovery and the assumptions made on the process guiding fundamentals[2]. If efficiency is not rejected, there is some support for efficienct markets and the particular hypothesis regarding fundamentals. If efficiency *is* rejected, then this only says that if the market was actually efficient, it did not follow the postulated pattern for fundamentals. Thus in case of a rejection, it is never possible to know whether markets are truly inefficient, or whether fundamentals were simply improperly specified.

The problem of observability is not specific to applied financial studies, but applies more generally to much of economics. For this reason, many branches of economics have taken to the use of experimental methods. The experimental method, in brief, is to construct and repeatedly observe behavior in a particular environment. As opposed to field studies, which consist of data that include all manner of unobservable influences, experimental studies use a relatively simple and “sterile” environment to focus in on the variable of interest.

The use of laboratory experimental methods makes the fundamental value directly observable. As with any choice of research methodology, however,

[2]Summers (1986) observes that many tests of the observable implications of market efficiency have low power to reject the null hypothesis of no mispricing. He writes “…certain types of inefficiency in market valuations are not likely to be detected using standard methods. This means the evidence found in many studies, that the hypothesis of efficiency cannot be rejected, should not lead us to conclude that market prices represent rational assessments of fundamental valuations. Rather, we must face the fact that most of our tests have relatively little power against certain types of market inefficiency. In particular, the hypothesis that market valuations include large persistent errors is as consistent with the available empirical evidence as is the hypothesis of market efficiency.”

the choice of the experimental method involves a tradeoff. The use of these methods typically restricts attention to the study of markets that are small in terms of scale, time, number of traders, and monetary stakes, and whose trader characteristics differ from those found in typical non-laboratory markets. However, experimental methods do have the advantage that they allow the fundamental value of an asset to be unambiguously specified, observed, controlled, and compared to transaction prices.

Therefore in addition to learning about markets by looking at data from stock exchanges and exchange rates, laboratory markets are also used to investigate bubble phenomena. Relatively simple markets are constructed in which subjects are able to buy and sell units of one or more assets. Then by varying various features of the environment, the impact of those features on the laboratory market offers suggestive evidence about how markets in general are affected by those features.

1.5 The Contributions of This Thesis

Market and bubble research may be approached from a multitude of angles. The first is to study the endogenous emergence of bubbles as a function of institutional market settings - which type of market conditions are more prone to bubble formation than others? Another line of research is to take the presence of bubbles as given, and then analyze the effect this has on other market activities. Finally, a third way issue is examine exactly which type of individual behavior causes bubbles to be formed.

This thesis consists of three experimental studies, each of which uses one of the approaches mentioned above to study bubble markets. To place this work into context, Chapter 2 describes the basic design of an experimental asset market, including the specific design used in the subsequent three chapters, and contains a review of previous literature that use variations of the setup to investigate experimental bubbles. The study chapters are independent of one another and may be read in the order most preferred by the reader.

Chapter 3 finds that the time path that fundamentals follow affects market efficiency. The notion of fundamentals affecting prices is largely accepted as being true, but the novelty of this chapter is that it shows that turning points in fundamentals can also affect efficiency. The chapter shows that markets perform more efficiently during downturns in fundamentals than they do during upswings. The implications of this asymmetry is that policy might need to be asymmetric as well.

Chapter 4 studies the creation and destruction of financial shares by firms through the use of share issues and share repurchases. The results show that a repurchase of shares increases the price of the asset, and a share issue decreases the price of the asset, compared to a benchmark of no intervention. The effects are consistent with the capital structure puzzle, a negative correlation that is typically observed between the price and the supply of shares of stock. Secondly, the empirical patterns observed are consistent with a model proposed by De Long et al. (1990), which posits three trader types– fundamental, speculator, and momentum– interacting in the market. Lastly, the downward pressure on prices resulting from share issues drives prices down toward, but not beyond, fundamental values. This downward resistance at the fundamental value arises from the impact of an intervention on the proportion of the total stock of units and cash held by each trader type.

A pressing issue in many parts of economics is how well theoretical models describe reality. Until only recently, this was done almost exclusively by comparing the choice predictions of the models to actual outcomes. However, there is now a burgeoning literature on *neuroeconomics* that uses recent development of physiological equipment and techniques to study the brain activity underlying choice decisions (see Camerer et al. (2005) and Glimcher et al. (2008) for good summaries of the field). For example, several studies look at how neural activation correlates with behavior in financial tasks (Preuschoff et al. (2006), Preuschoff et al. (2008), Knutson and Bossaerts (2007), Hampton et al. (2008)).

In this vein, Chapter 5 is a study of information absorption in bubble markets and how this relates to subsequent choice behavior. Using advanced eye-tracking techniques, an experiment is conducted that tracks screen focus as individuals trade in a market. With respect to design considerations, there is some evidence that only certain types of dividend information affects price discovery. In terms of explaining the eye-tracking data, information acquisition is found to be stable across a variety of socio-demographic measures. The final piece of analysis uses the eye-tracking data to predict short-term individual and market behavior. Attention to received dividends is found to play a prominent role both in terms of future price increases and in terms of individual trading patterns. Market crashes are found to be preceded by a sharp drop in attention to buying opportunities, while once crashes are underway attention tends to return to the purchasing area of the screen.

The recent convulsions in the global economic system have shown that there are strong concerns regarding the ability of the market system to "get things right". This thesis is a small step forward towards better understanding that system and improving its performance.

CHAPTER 2

BACKGROUND

The following three chapters describe controlled laboratory studies of experimental bubble markets. As such, this chapter serves as a primer on the topic, including a discussion of their design parameters and previous research covering the topic. Finally, the section concludes with a summary of the common design elements found in the ensuing chapters.

2.1 Terminology

An asset market *study* or *experiment* consists of a set of independent observations of a market setting. An *observation* refers to the actions of a distinct group of subjects in an isolated market. When multiple market designs are used in a single study, each design is referred to as a *treatment* of the market, and the various treatments usually differ from one another along a single dimension. This allows the effects of changes along that one dimension to be measured by differences in behavior between observations from different treatments.

A *session* refers to a specific time period when observations are collected. When, as is often the case with asset market experiments, a single session is used to collect a single observation, the terms “observation” and “session” may be used interchangeably. This is the case with the work discussed in this book, therefore unless otherwise noted, “session” will also refer to an independent market observation.

2.2 Initial Studies

2.2.1 The Beginning

Market experiments began by studying the price properties of markets for goods that were valued differently by each market participant, and in which subjects had different information sets regarding the fundamental value. The use of a range of participant values for the good provided a seemingly-necessary impetus for trade and also allowed for the study of the re-allocative efficiency of the market[1].

Chamberlin (1948) reported the first results of an asset market experiment. Wanting to illustrate a theoretical argument to his students, Chamberlin had them participate in a market for an artificial asset. Students began by drawing numbered cards from a randomly stacked deck. The number was the redemption value of the good to the student. The idea was that students with low values (designated as "sellers") would sell a unit of the good to those with high values ("buyers"). Each student was able to participate in a single trade only, thus the market produced a series of transaction prices until there were no subjects left in the market who still wished to trade. The induced valuations for the good implicitly defined market demand and supply curves, and thus also a competitive equilibrium (unknown to the market participants) which actual volume and transaction prices could be compared to.

The markets were generally efficient at transferring goods from sellers to buyers, although prices did tend to be a bit too low and volume a bit too high relative to the competitive benchmark. It was, however, the process of seeking to explain these slight anomolies that led Chamberlin to question the very premise of how markets might generally equilibrate. He writes (p. 102):

> "My own skepticism as to why actual prices should in any literal sense tend toward equilibrium during the course of a market has been increased not so much by the actual data of the experiment before us - which are certainly open to limitations - as by failure, upon further reflection stimulated by the problem, to find any reason why it should be so."

He explains by noting that (p. 102, emphasis in original):

> "...information during the market as to the *equilibrium* price would help establish a trend in that direction, but information as to *actual*

[1] Smith et al. (1988) would later show that neither heterogeneous asset values nor different information sets were necessary to generate substantial market exchange.

> prices may do the opposite, in so far as they are divergent from equilibrium and are falsely interpreted to be near it."

The point he makes in the second quotation is that prices may perpetually drift farther and farther from the fundamental value, since fundamental values are not known in the real world. If actual prices are not near fundamentals, but are *interpreted* as so, this can lead to a reinforcing divergence of prices from fundamentals. What he had just described, in fact, was a distinguishing feature of a bubble episode.

Market experiments had begun, and the possibility of directly observing a bubble did not seem far-fetched. However, following Chamberlin's musings on the likelihood of bubble phenomena, the issue lay dormant for another 40 years while the attention of the literature remained more focussed on performance near the competitive equilibrium. Various results were obtained regarding the sensitivity of market environments to different factors[2] , although no bubbles were ever observed.

2.2.2 A First Sighting

The original idea of Smith et al. (1988) (hereafter SSW) had been to determine a set of sufficienct conditions for generating a bubble. The idea was to start with a simple design that did not produce a bubble and then modify the environment until a bubble was observed. The authors studied a similar market as the original Chamberlin (1948) study and other subsequent papers, with a few key differences. First, earnings from asset holdings were paid out periodically throughout the life of market, rather than only at the end of the market. Second, only the distribution of possible values was known to subjects (a combination of draws from a four-point uniform distribution). Third, this distribution was identical across subjects and common knowledge. This generated a fundamental value for the asset, common to all subjects, that declined linearly over time[3]. Finally, subjects were permitted to enter into as

[2]For example, rent size and trading mechanism (Smith (1964)), speculation (Miller et al. (1977)), transaction costs (Noussair et al. (1998)), price controls (Isaac and Plott (1981)), the presence of futures markets (Forsythe et al. (1982)), the number of assets (Plott and Sunder (1988)), production decisions (Mestelman and Welland (1988)), market power (Isaac et al. (1984)), hidden trading (Campbell et al. (1991)), private information (Plott and Sunder (1982)), expectations (Williams (1987)), and experience (Forsythe et al. (1982)).

[3]Strictly speaking, the fundamental value is only equal for all subjects up to a risk-adjustment factor, although given the stakes of the experiment and the repeated nature of the dividend draws, these factors are likely of secondary importance.

many trades as they desired (as long as cash and asset holdings were never negative).

What they found was that their simple environment already produced bubbles! The pattern of price deviations they were able to consistently observe in their markets fit exactly the description of a bubble - a sustained period of increasingly higher over-pricing occured in the early and middle periods of the market[4], until finally markets crashed abrupty in the latter periods. The SSW experiment is particularly noteworthy because they were able to consistently reproduce the bubble phenomena that up until that point in time had never been directly observed with certainty.

Given that they already had an environment that generated bubbles on their hands, they then set about determining what, if anything, could eliminate them. They considered price controls and the type of subjects used in the market. Markets consisting of people from the local business community and markets using top-performing subjects from previous experiments both produced bubbles. Price controls had little to no effect. The only procedure that seemed to significantly reduce bubbles was when the same group of subjects repeated the market environment. As a first attempt at characterizing the process underlying a bubble, the authors also included four sessions that included subject forecasts of future prices. They found that forecast errors are inversely related to price changes, that is subjects tended to under-predict expansions and over-predict contractions, but expectations also adapted over time.

2.3 Variations

Thus an environment in which bubbles could be reliably produced had been discovered. This spawned several other studies that increased understanding of how and why bubbles occur by considering derivations of the original setting studied by SSW.

This section presents a brief summary of that research. Some earlier summaries of experimental asset markets in general are provided in Smith (1991) and Sunder (1995). For slightly different perspectives on the findings, Bossaerts (2001) analyzes the literature through the lens of asset pricing theory, while Gerding (2007) discusses the implications for legal policy. Most recently, Plott and Smith (2008) contains papers discussing a large selection of the work dis-

[4]A *period* here simply indicates the period of time before units of the asset produce dividend earnings for their owners.

cussed below.

The basic treatment for studying asset markets consists of the following. First, all subjects of a session are endowed with units of cash and shares of one or more assets. Subjects value assets because 1) assets generate cash earnings for their owners, and 2) assets may be sold to other subjects. Following the endowment of shares and cash, subjects are able to make trades involving shares and cash in a market according to some trading mechanism, and under certain informational constraints. This process of endowment followed by trading may then be repeated. Finally, subjects are compensated according to their performance in the session.

To summarize, typical parameters describing a treatment are: 1) the number and types of subjects used, 2) the number of assets and their values to subjects, 3) the type of trading mechanism used, and 4) the number of times the endowment and market cycle is repeated. What follows is a brief description of each of these elements, including possible values and their effect on the basic SSW bubble environment.

2.3.1 Subjects

Number of Subjects

The number of participants in the market can range from one (trading against an automated counter-party, as in Feldman and Friedman (2008)), to several hundred or thousand (as in Drehmann et al. (2005), who conduct an internet experiment for the study of thick markets).

Subject pool

The most common type of subject used in asset market experiments are undergraduate university students. There are at least two reasons for this. The first is that they provide an ample source of reasonably well-educated, yet still inexpensive, supply of labor for running sessions. The second is that since they are readily available to many researchers, they provide a common population for replicating findings. Subjects may be selected according to many attributes, including traditional socio-demographic variables such as years of education and ethnicity, but also according to level of experience (in both experiments and/or trading environments).

The SSW study includes sessions that utilize members of the local business community, yet they still find substantial bubbles. Cheung and Palan (2009) find that males tend to behave more extremely in the bubble market setting.

2.3.2 Assets

Number of Assets

Subjects are endowed with one or more types of assets that they are able to trade for cash. In most cases, there is only one type of asset, however it is not uncommon for multiple assets to exist. A special case of multiple assets is a *futures market* (see below).

Multiple Markets

Various authors have studied how the simultaneous presence of multiple markets affects bubble formation. Fisher and Kelly (2000) study an SSW design, but with two tradeable assets. They consider various treatments that vary the variability of the returns from the two assets. In general they find that both markets tend to bubble and crash at the same time, although they find that bubbles are larger for riskier assets, a result also confirmed in Ackert et al. (2002).

Futures Markets

Noussair and Tucker (2006), building on the work of Porter and Smith (1995), consider the effect of the presence of futures markets on market performance. Futures markets are markets in which contracts are agreed upon in the present regarding the future sale and purchase of goods. Given the tendency of experimental markets to end with little mis-pricing, the authors hypothesize that futures markets would help agents backward induct pricing at fundamentals earlier in the market. So in addition to the ability to make trades in the current spot market, subjects were given the opportunity make trades in future markets pertaining to periods of time between all remaining earnings payments (Porter and Smith considered a more limited set of future markets). They find that sufficient futures trading capacity is very effective at inducing pricing at fundamental values.

2.3.3 Valuation Mechanism

One of the reasons subjects may value shares is because shares generate earnings for their owners. Uncertainty may (in the case of random dividends) or may not (in the case of certain dividends) exist in a subject's earnings distribution. The distribution may also vary across subjects (as is the case in Chamberlin (1948)) and time (as is the case in Chapter 3). Shares can also differ in their dividend frequency: typically earnings are generated either only once at the end of the market, or at regular intervals during the market.

The valuation mechanism is particularly important because it defines the competitive equilibrium, or fundamental, values for the assets. Specifically, the intersection of the demand and supply curves associated with expected earnings for each trader define a competitive equilibrium price at which trading will take place. This is equivalent to the expected earnings on a share from the median trader. In the special case where all traders face the same distribution of earnings on a share and are risk neutral, the competitive price is equal to the expected earnings of all traders.

Porter and Smith (1995) find that eliminating the uncertainty from dividends does not eliminate bubbles. van Boening et al. (2000), however, show that breaking up a single dividend payment into smaller payments increases bubble size. Specifically, large bubbles are observed when dividends are paid periodically throughout the market, whereas very little over-pricing occurs when only a single terminal payout is used. Noussair et al. (2001) show that the result pertaining to markets with a single terminal value is not the result of having a market with constant fundamentals, but is instead caused by the form of the dividend payments. The study finds that bubbles can easily occur in markets with constant fundamentals and regular earnings payouts. Most recently, Lei and Vesely (2009) find that substantial experience with dividends before the opening of the market eliminates bubbles.

2.3.4 Trading Mechanism

Type of Interaction

The interaction between subjects may either take place in person, electronically in a local computer laboratory, or completely anonymously (via the Internet, for example). Additionally, trading may take place in a centralized exchange, or through smaller group (or pair-wise) exchanges. Finally, there are various ways in which market information may be presented to subjects. The simplest way in this day and age is to present everything using a computer interface. Before the advent of computerized trading interfaces, however, subjects were often presented with physical cards containing information regarding the properties of the asset and their trading opportunities.

Trading Institution

The most popular choice of trading institution is the type of institution orginally studied by SSW. These are auction markets, where one or both sides of the market post and accept offers. Another popular institution is a "call" (or "sealed-offer") market, where both sides of the market submit sealed offers that then generate a market clearing price according to some matching method (see, for example, Boening et al. (1993)). Lugovskyy et al. (2009) study bubbles and crashes in the presence of a *tâtonnement* pricing mechanism. Tâtonnement is a system in which bids and offers are successive matched until an equilibrium price is reached (where demand equals supply). The previous authors show that such a pricing mechanism, which allows for substantial learning regarding equilibrium values, significantly mitigates bubbles sizes.

Trading Restrictions

Restrictions may or may not include 1) the ability to only buy or only sell shares, 2) the inability to borrow cash or shares, 3) restrictions on permissable prices, 4) restrictions on the number of units that may be bought or sold, and/or 5) the ability to participate in futures markets.

The specific case of common share valuations is particularly interesting since the only seemingly rational reasons for trading under these conditions are due to 1) speculation and 2) the re-allocation of risk. Lei et al. (2001) examine essentially the same market design as Smith et al. (1988) but with an additional treatment - a design in which one half of the subjects are restricted to only selling shares and the other half is restricted to only buying. Under these conditions, speculative behavior is essentially eliminated as a trading motivation since no subject is able to purchase with the hopes of re-selling in the future to someone else at, for example, a higher price. This means that theoretically the only reason left to trade is the (relatively mild) inclination to re-allocate risk.

What they find, surprisingly, is that bubbles still result! They report a substantial number of share purchases for prices higher than the maximum amount of potential dividends. They further investigate whether the bubbles can be explained by some experimenter-induced effect that causes subjects to trade by opening single-period markets simulatenously for the duration of the first market. As expected, this reduces the impetus for subjects to be biased towards trading in the first market, however this does not eliminate the bubble pattern from prices. This is supported by the findings that taxes on trades (King et al. (1993)) and capital gains (Lei et al. (2002)) are not effective at pushing prices closer to fundamentals. The conclusion of this work is that at least some part of bubble outcomes is due to irrational behavior, and not completely due to speculation.

Short selling is the act of "borrowing" and selling units of the asset in the present, in exchange for the obligation to purchase them at a later date. Without short selling, a trader who thinks that prices will fall in the future can only sell all of their share holdings and wait for prices to fall. With short selling, they can "borrow" more shares and sell them if they so desire, effectively increasing the opportunity to speculate that prices will fall.

Haruvy and Noussair (2006) examine the effect of a variety of short selling rules. One comparison they make is between a treatment without short selling and treatments with a short selling capacity of various units per trader. They find (contrary to King et al. (1993), who study a weaker relaxation of the short selling constraint) that sufficient short selling capacity significantly decreases price levels. In effect, their results suggest that bubbles are sensitive to the ability of traders to speculate in the downward direction. This is in accord with other previous findings for both bubble (Ackert et al. (2002)) and non-bubble asset markets (Vorsatz and Veiga (2008)), but a novel finding is that short selling may not always push prices to fundamental values. It may, in fact, create reverse-bubbles! From the results on short selling and the previous results on speculation, the picture that emerges is that how strong of an effect speculation has on the bubble formation process is still an open question.

2.3.5 Repetition

The first market in a session may be followed sequentially by another similar market. At the end of the first market, subjects are endowed with new units of cash and shares and then participate in the next market, that may or may not exactly replicate the previous market. Variations on this theme include mixing subjects across sessions of the same treatment, either with subjects of the same or different experience level.

Building on the original results reported in SSW, various authors have continued to study the role of experience and expectations during bubble markets. Boening et al. (1993) confirm the dampening effect of experience on bubbles in the context of posted-offer markets, while Dufwenberg et al. (2005) verify that bubbles in mixed-experience markets are rare.

Haruvy et al. (2007) offer a rigorous confirmation of the effect of experience on convergence in a study designed to study the adaptive behavior of traders' beliefs. Specifically, they use the SSW design with the four consecutive markets. In the six sessions they report, they observe large bubbles in the first market and steady convergence to fundamentals in the three subsequent markets. Traders' beliefs about future prices tend to be closely related to their experience in previous markets. That is, traders tend to expect that what occurred in previous markets will repeat itself in future markets. Perhaps not surprisingly, however, these beliefs consistently over-estimate the duration and size of the subsequent bubble. The intuition for this is that if everyone expects a bubble to pop at a particular level and time, everyone will begin selling off their shares just before that particular level and time, thus meaning that the market crashes earlier than everyone had expected.

The results of this section tend to give the impression that repeated market experience is effective at eliminating bubbles. However, Hussam et al. (2008) find that bubbles can be "rekindled" if experienced groups of traders participate in an environment with substantially different parameters than the one in which they gained their experience. This suggests that subjects might not actually be "learning" to correct irrational behaviors, but instead adjust their trading behavior as a best-response to a belief that future markets will display price patterns similar to those they have already experienced.

2.4 Structure of the Study Chapters

Since the original work by Smith, Suchanek and Williams, a plethora of studies have joined the hunt to figure out what makes market bubbles "tick". The previous section has sketched the basic anatomy of a bubble experiment and surveyed some of the findings related to their study. The chapters that follow deal with many related topics: Chapter 3 is an investigation of how dividend streams can affect price discovery, Chapter 4 considers how firm interventions in the market can influence the bubble formation process, and Chapter 5 is a closer examination of how subjects' use of the trading environment is related to aggregate price movements. As each of these chapters contains an experiment on bubble markets, they share many common features. These include the presentation of the study itself, the design of the underlying experiment, and methods used in analyzing the experimental data. Each of these features is discussed in more detail below.

2.4.1 Presentation

Each of the following three study chapters essentially have the following structure. They begin in Section 1 with an introduction to the particular topic at hand. This is followed in Section 2 by a list of the specific hypotheses related to the topic. Section 3 presents the design of the experiment and Section 4 discusses its results. Section 5 briefly summarizes the main points of the study and provides some concluding remarks.

2.4.2 Design

The experimental protocol, based on the Smith et al. (1988) study, is as follows.

No subject participated more than once in an experiment. Sessions were conducted in English at Tilburg University. Markets were computerized and used continuous double auction trading rules implemented with the z-Tree computer program (Fischbacher (2007)) developed at the University of Zurich. Subjects were students enrolled at Tilburg University, typically undergraduates in economics and business.

In each session, N subjects participated in one or more sequential markets, all identical in parametric structure. Every subject began all markets of a session with a particular endowment of cash (referred to during the experiment as "francs") and units of an asset. Initial cash and asset endowments were chosen to approximately equalize expected earnings across all sessions, although actual realized earnings at the individual level depend on the distribution of asset holdings, the dividend realizations, and the trading strategies employed. Subjects knew their own initial endowments, but not the initial endowments of others.

For the duration of each market, subjects were able to trade units of the asset for cash amongst themselves by placing and accepting orders from an open order book. Borrowing and short selling were not allowed. "Francs" were used for all transcations and payments within a market. Trades were for a single unit of the asset at a time.

This meant that at any time subjects could submit an offer to the market, provided that they had sufficient cash or units to fulfill their part of the transaction. An offer specifies a price at which the agent is willing to either buy or sell a share. Any trader with sufficient funds and units of asset to complete the transaction may accept any outstanding offer at any point in time. All offers were displayed to all agents on their computer screens. Upon acceptance of an offer, a trade was conducted and the asset and cash transferred between

Table 2.1: Design Parameters

Parameter	Value
T, number of periods	15
distribution of dividends	uniform from $(0, 8, 28, 60)$
N, number of subjects	9

the transacting parties.

The duration of the market was divided into T periods of equal length. At the end of each period, the asset paid a dividend that was immediately added to cash holdings. The dividends were independently drawn from a distribution that was identical for all periods and units of the asset. Thus, in any period the expected dividend on a unit of the asset was equal to the expected value of the dividend distribution. Because the dividends were drawn independently each period, the expected future dividend stream in period t, $\sum_{i=t}^{T} E(d_t)$, equaled the expected period dividend multiplied by the number of periods remaining in the life of the asset, so that $\sum E(d_t) = (T - t + 1)E(d_t)$. When dividends were the only source of intrinsic value for the asset (Chapter 3 is an exception), in period t the fundamental value f_t of the asset equaled the expected future dividend stream. In other words:

$$f_t = \sum_{i=t}^{T} E(d_t) = (T - t + 1) \cdot E(d_t).$$

The payment of a dividend at the end of a period reduced the fundamental value by $E(d_t)$ francs immediately after the payment, since the number of future dividend payments decreased by one.

Inventories of assets and cash carried over from one period to the next. Thus for each individual, the quantities of cash and assets held at the beginning of period $t + 1$ were the same as those held at the end of period t, adjusting for any dividends received.

Earnings

A subject's entire earnings over a market were equal to the amount of "francs" he held at the end of that market. A subject's earnings for the entire experiment were then equal to the sum of his earnings from each of the markets of the session, plus an additional participation fee. Francs were converted to Euros at a pre-announced rate.

Sequence of Events

The experimenter first distributed and read aloud a detailed explanation of how to make and accept offers with the electronic trading interface. This took approximately five minutes. For the next ten minutes subjects practiced trading using the interface. Activity during this phase did not count toward final earnings. After the practice phase was completed, the rest of the instructions, which described all other aspects of the experiment, were handed out and read aloud by the experimenter. Subjects were then assigned their initial portfolios of cash and shares and the (first of potentially many) market(s) for the asset was conducted. At the end of a session, subjects were called out of the room one by one and paid anonymously for their participation in the session.

2.4.3 Notation

When a variable only has one subscript, for example x_t, Δx_t will be defined as the first difference of that variable, so that $\Delta x_t = x_t - x_{t-1}$. When a variable has more than a single subscript, for example $x_{m,t}$, the subscript on Δ will indicate the subscript with respect to which the difference is taken. For example, $\Delta_m x_{m,t} = x_{m,t} - x_{m-1,t}$ and $\Delta_t x_{m,t} = x_{m,t} - x_{m,t-1}$. Where possible, subscripts will be suppressed for clarity.

2.4.4 Analysis

Each study consists of a series of observations, or sessions, of an asset market setting. For period $t \in (1, \ldots, T)$ of session i, let f_t^i denote the fundamental value of the asset and let p_t^i denote the observed period median transaction price.

Two measures of mispricing formally introduced by Haruvy and Noussair (2006) are *Dispersion* and *Bias*. Both depend on the *period bias*, which is the difference between the median transaction price p_t and fundamental value f_t in period t of session i e.g. $bias_t^i = p_t^i - f_t^i$. Formally, the measures of mispricing are defined as follows:

$$\begin{aligned} Dispersion_i &= \textstyle\sum_t |bias_t^i| \\ Bias_i &= \textstyle\sum_t bias_t^i \end{aligned}$$

Dispersion is a measure of overall discrepancy between prices and fundamentals, where larger values indicate larger differences between prices and fundamentals. *Bias* is a measure of systematic over-or under-pricing, where higher values indicate higher prices, and where a value of zero reflects equal average prices and fundamentals. Lower values of *Dispersion*, which has a lower bound of zero, are interpreted as more effective price level discovery. Values of *Bias* closer to zero are similarly interpreted as indicating better price level discovery.

One sees great things from the valley; only small things from the peak.

Gilbert K. Chesterton

CHAPTER 3

PEAKS AND VALLEYS: MARKETS WITH NON-MONOTONIC FUNDAMENTALS[1]

This chapter reports the results of an experiment designed to measure how well asset market prices track fundamentals when the latter experience peaks, and alternatively, troughs. The speed of the price discovery process, whereby markets converge to fundamental values as the market is repeated, is observed to differ between the two treatments. The process is more rapid and complete in markets in which fundamentals rise to a peak and then decline, than in markets in which fundamentals decline to a trough and undergo a subsequent increase. The findings demonstrate that the characteristics of the time path of the fundamental value can influence the degree to which prices track fundamentals.

3.1 Introduction

The conjecture investigated here is that the tendency for an asset to track its fundamental value depends on properties of the time-profile of the fundamental, because under some profiles the process of price discovery is slower and less complete.

A feature of many economic time series is that they experience peaks or troughs, and thus experience periods of rising value followed by periods of

[1]This chapter is based on Noussair and Powell (2010).

decline, or rather episodes of increasing value that follow a decline. Despite the fact that such a structure is common, and that such market peaks and troughs are often optimal times to trade, markets with these properties have not to date been investigated with experimental methods. This chapter reports the results of an experiment designed to directly compare, in a controlled manner, the behavior of (i) markets for assets that experience a period of increasing, and then a period of falling, fundamentals, versus (ii) markets in which fundamentals first decline and then rise.

The first type of market is referred to as a *Peak* market, and the second as a *Valley* market. The *Peak* and *Valley* markets are symmetric in the sense that the assets are traded over an equal time horizon, experience a peak or trough in fundamental values of equal magnitude compared to initial and final values, and experience their extreme fundamental value at the same time. Thus, the experiment is designed so that there is an opportunity for asymmetries in the reaction of prices to peaks and troughs in fundamentals to appear and to be identified. The existence of a pricing asymmetry would be consistent with an intuition that has been expressed by some policymakers with regard to the behavior of macroeconomic variables[2].

The extent to which price discovery has occurred is measured with three different indicators: (a) the magnitude of the differences between price levels in the asset markets and the underlying fundamental values, (b) the consistency with which price trends reflect trends in underlying fundamentals, and (c) the difference between the timing of peaks and troughs of prices and those of fundamentals. The design, in which the same individuals participate in four sequential markets, allows for the study of how differences between treatments, with regard to the pricing accuracy measures above, evolve with repeated interaction in a sequence of markets.

The findings are that markets that experience a peak have a stronger and more rapid tendency to converge toward fundamental pricing as traders gain more experience than markets that undergo a trough. Thus, in the markets

[2]This intuition has been voiced, for example, by former US Federal Reserve Chairman Alan Greenspan who in a recent interview indicated "What strikes me about the current period is it's wholly consistent with my generalized view of how important innate human characteristics are in sustaining the business cycle. I've always been concerned that in setting up an econometric model you take history irrespective of whether it's up or down, and there's an implicit judgment that the coefficients work symmetrically on the upside and downside. There is a general belief, for example, that capital gains on homes have a buoyant effect on consumption going up and precisely the same on the other side. I'm beginning to question whether that premise is true" (Alan Greenspan, Sept. 17, 2007).

studied here, the likelihood that an asset market tracks fundamental value depends on the process that fundamentals follow. In other words, one environment is more conducive to pricing at fundamentals than the other, simply because of the interaction between the trader behavior that appears in asset markets and the particular process guiding the time path of fundamentals. The consistency between prices and fundamentals depends not only on previously identified factors such as the market institutions in place, the regulatory framework, and the number, experience level, and sophistication of traders, which are all controlled for in these markets, but also on the time path of the fundamental values.

The assets studied in this literature are almost exclusively finitely-lived, pay non-negative dividends at regular intervals, and are created in settings where no alternative interest-bearing investments exist. This means that the assets have fundamental values that decrease monotonically over time[3]. For this special case of declining fundamentals, the literature has yielded consistent results about the behavior of asset prices (see Chapter 2). The current study appears to be the first experimental study in which the behavioral properties of markets experiencing a peak or trough in fundamentals are investigated.

3.2 Hypotheses

The hypotheses concern the differences between two different experimental treatments, *Peak* and *Valley*, with regard to various criteria of effectiveness of the price discovery process. Effectiveness of price discovery refers to consistency between prices and fundamentals, and how this consistency evolves as the market is repeated and as traders gain more experience.

The degree of consistency between the prices and fundamentals is calculated in terms of three criteria: (1) levels, (2) trends, and (3) timing of changes in trend.

The first treatment comparison is with respect to price *level* discovery: the difference between price levels and fundamentals over the life of the asset. *Bias* and *Dispersion* are used to measure whether price levels track fundamental value to the same extent across treatments. Hypothesis 1 is that the distribution of price level discovery, taking each session as an observation, does not

[3]Experimental studies of long-lived asset markets have focused almost exclusively on the case of monotonically decreasing fundamental values, with a few exceptions (Camerer and Weigelt (1993); Noussair et al. (2001); Ball and Holt (1998)) that study assets with constant fundamental values.

differ significantly between treatments.

Hypothesis 1 *Price levels track fundamentals equally closely in the two treatments.*

While Hypothesis 1 is concerned with price levels, Hypothesis 2 addresses a similar question about the relationship between *trends* in prices and fundamentals. In an efficient market, price trends send accurate signals to investors and observers about whether the intrinsic value of an asset is currently increasing or decreasing. The question considered here is whether prices are equally likely to move in the same direction as fundamentals in the two treatments. Let $TD_t^i = 1$ if $sign(\Delta p_t^i) = sign(\Delta f_t^i)$ and 0 otherwise, and define $TD^i = \sum_t TD_t^i / T$. The variable TD^i, referred to as *trend discovery* (TD), measures the percentage of periods in session i in which current price changes are in the same direction as current fundamental value changes. Greater values indicate better discovery of the underlying trend in fundamentals and the upper bound of 1 corresponds to movement of prices and fundamentals in the same direction in all periods. A test is conducted for whether or not trend discovery differs between treatments corresponds to the following hypothesis.

Hypothesis 2 *Price trends are equally consistent with trends in fundamentals in the two treatments.*

Whether or not the observed price vector accurately reflects the time at which prices attain their extreme value (maximum in *Peak*, minimum in *Valley*) is also considered. This period is referred to as the turning point of prices and is compared to the turning point in fundamentals, which is the analogous period for the fundamental value process[4]. For Valley sessions, let $t_i^* = \arg\min_{t \in (2,\ldots,T-1)} p_t^i$, and let $t_i^* = \arg\max_{t \in (2,\ldots,T-1)} p_t^i$ for Peak sessions. t_i^* denotes the turning point in prices in session i. Furthermore, define periods $t_i^{'} = \arg\min_{t \in (2,\ldots,T-1)} p_t^i$ for Valley sessions, and let $t_i^{'} = \arg\max_{t \in (2,\ldots,T-1)} p_t^i$ for Peak sessions. Period $t_i^{'}$ is called the turning point in fundamentals in session i and the turning point of fundamentals is said to have "been discovered" if $t_i^* = t_i^{'}$, so that a price peak (trough) signals that the asset's value has also reached a maximum (minimum). The *turning point* discovery of session i is defined as $TP_i = |t_i^* - t_i^{'}|$. Smaller values, which are closer to the lower bound of zero, indicate better turning point discovery. Hypothesis 3 is that the distribution of turning point discovery, by session, is similar in the two treatments.

[4]In the analysis that follows, the actual fundamentals in a session is used to calculate all measures and in conducting all statistical tests, taking into account the slight differences in fundamental values between sessions V1-V2 and V3-V5.

Hypothesis 3 *The time difference between the turning points of prices and turning points of fundamentals is the same in the two treatments.*

As described in more detail below in Section 3.3, each experimental session consists of several repetitions of an asset market with the same participants. This repeated market feature allows hypotheses 1 - 3 to be evaluated seperately for each of the resulting experience levels. It also allows the groups to be tracked over time and the effect that repetition of the market has on the price discovery measures to be considered. Specifically, whether or not price discovery improves at all with repetition in the market is considered, and if so, whether or not it also improves at a similar rate in both treatments. Let the subscript m on a price discovery measure index the repetition of the market, so that D^i_m, B^i_m, TD^i_m, and TP^i_m denote dispersion, bias, trend discovery, and turning point discovery, respectively, in market m of session i. The null hypotheses advanced here is that repetition improves all measures of price discovery, and that it does so at a similar rate in both treatments.

Hypothesis 4 *Price discovery increases with repetition.*

Hypothesis 5 *The rate of improvement in price discovery is identical in the two treatments.*

3.3 Experimental Design

The experiment had two treatments, called *Peak* and *Valley*. The *Peak* treatment was characterized by a time path of fundamentals that was increasing during the first half of each market and decreasing during the second half. In *Valley* sessions, fundamentals first declined and then recovered. In all cases, the fundamental value attained an extremum in period $T/2$ of each market.

The fundamental value of the asset arose from three sources: dividends, taxes, and a final buyout (a payment for each unit of asset held at the end of the market to the unit's owner). These were payments to or by the current owners of the asset on each unit they held. At any point in time the fundamental value was the sum of the expected future payments from all three sources. Specifically, the fundamental value of a unit of the asset during any period was equal to the sum of the expected dividends and final buyout it would generate, minus any taxes that remained to be paid on the unit. Thus, the fundamental value of one unit of the asset at any point in time was the expected value of the stream of future payments that would result from holding the unit for the remainder of the current market. The three different sources of value were included in the design merely to induce the appropriate dynamic patterns in fundamental values[5]. The number and timing of future dividend draws, tax payments, and final buyouts in the current market was always common knowledge.

Certain periods of each market were tax periods. After every tax period, subjects paid a fixed inventory tax for each unit in their possession. Due to the fact that the size of the period tax was always larger than the expected dividend, the difference between the expected dividend to be received and the tax to be paid during tax periods was always negative. Thus, after each tax period, the fundamental value increased, as the future liability on each unit of the asset decreased.

The third determinant of the fundamental value was the final buyout, or terminal value, of the asset. Each unit yielded a final payment at the end of the market, in addition to any dividends and taxes that were collected and paid. The final buyout value increased the fundamental value of the asset for the entire life of the asset. Its sole purpose was to ensure that the asset always had a positive fundamental value.

Thus f_t^i, the fundamental value in period t of session i, equaled

$$f_t^i = \sum_t^T E(d_t) - \sum_t^T \tau_t^i + B^i, \tag{3.1}$$

where d_t and τ_t^i denote the dividend and the tax in effect in period t of session i and B^i is the final buyout or terminal value.

A number of consecutive markets were conducted within each session. Subjects started each market with their initial portfolio of assets and cash. Thus markets within a session were *ex-ante* identical, except for the prior experience level of the participants. Parameter choices are given in Table 3.1.

Thus the *Valley* treatment consisted of markets in which the fundamental value was decreasing in the early periods of the market, and increasing in later periods. In two of the *Valley* sessions (V1 and V2), the trough of fundamentals occurred in period 9, whereas the trough occurred in period 8 for the other three sessions (V3 - V5)[6]. The time path of fundamentals in the two treatments is illustrated in Figure 3.1. At all times subjects knew what the

[5]The same pattern could have been achieved solely through an appropriately specified dividend process. However, this would have required a non-stationary dividend distribution that included negative "dividends", an unfamiliar concept that participants might find more difficult to grasp.

[6]The same pattern could have been achieved solely through an appropriately specified

Table 3.1: Design Parameters

Parameter	Value	
	Peak	*Valley*
period length	120 seconds	
exchange rate	400 francs = 1 Euro	
number of consecutive markets	4	
τ_t, tax amount	48	
initial portfolios (shares, cash)	(3, 1233) (2, 1257) (1, 1281)	(3, 729) (2, 921) (1, 1113)
tax periods[a]	$1, \ldots, 7$	$9, \ldots, 15$
B, buyout value	0	216

[a] Tax periods in sessions V1 and V2 are periods $8, \ldots, 15$.

fundamental value would be in all future periods, and thus the change in the trend of fundamentals could be fully anticipated. The instructions provided to subjects are given in Appendix 3.A.
Dividends and final buyout payments were added to individuals' cash balances at the time they were paid, and taxes were subtracted from cash balances at the moment they were incurred. This meant that dividend payments added to and taxes subtracted from the cash that could be used for subsequent purchases.

In addition to the common design described in Chapter 2, at the end of markets one, two, and three, subjects were informed that their next task in the experiment would be to participate in another market identical to the one they had just finished.

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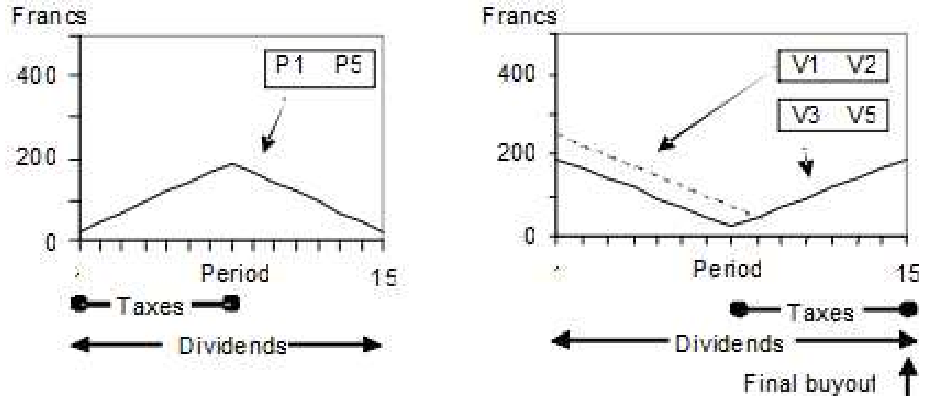
dividend process. However, this would have required a non-stationary dividend distribution that included negative "dividends", a concept that was felt would be more difficult for participants to comprehend.

Figure 3.1: Time Paths of Fundamentals



3.4 Results

Figure 3.2 shows the time series of median transaction prices by period in each of the *Peak* and the *Valley* sessions, respectively. The bold lines indicate the fundamental value. Each of the time series of data corresponds to one session. Overall, the figures indicate that (i) prices are usually higher than fundamental values, (ii) prices deviate less from fundamentals as traders become more experienced, (iii) prices track fundamentals more closely in later than in earlier periods within a market, (iv) deviations from fundamentals are larger in the *Valley* than in the *Peak* treatment and (v) repetition of a market decreases price deviations more in *Peak* than in *Valley*[7].

In markets 1 and 2 of the *Peak* treatment, shown in panel *a* of Figure 3.2, prices are usually greater than fundamentals in the early periods of the market, and then operate at close to fundamentals in the latter periods. Sessions 2 and 4 experience particularly large booms[8]. By market 4, prices track fun-

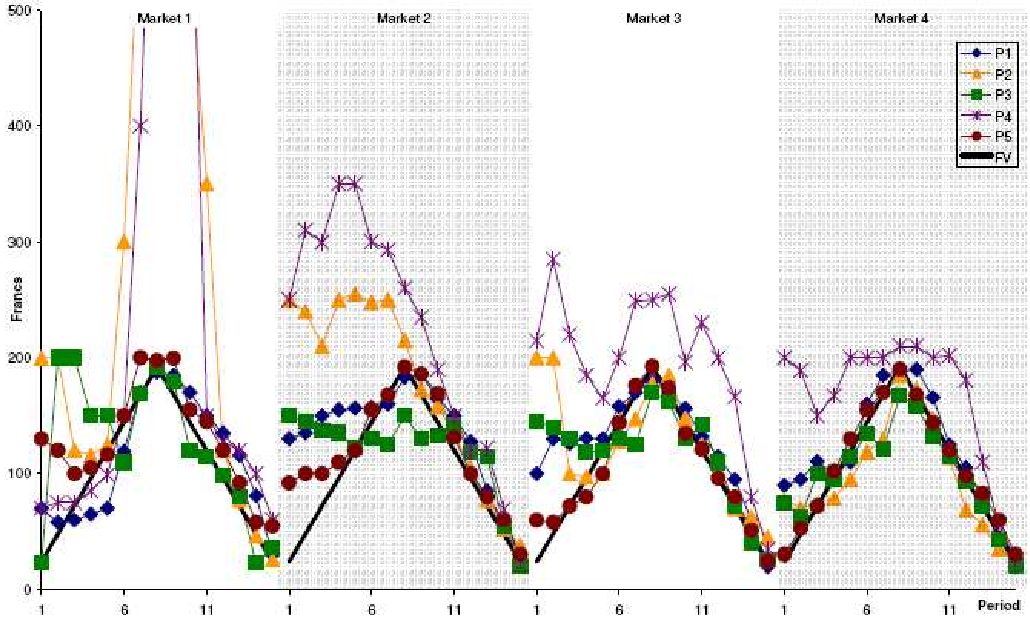
[7]The data on the volume of trade indicate that all of the markets were thick and active. Consider market Turnover, a measure of market activity employed in the analysis of experimental markets (King et al., 1993; Van Boening et al., 1993; Porter and Smith, 1995). Turnover equals the total volume of trade over the T-period market horizon, divided by the total stock of units, which is the total inventory of units of asset all individuals hold. Table 3.7 in Appendix 3.A reports the value of *Turnover* for each of the ten sessions of the experiment. The table indicates that in the *Peak* treatment, the average value (across sessions) of *Turnover* is 7.8 in market 1, and declines to 2.6 by market 4. In the *Valley* treatment, the average value is 7.8 in market 1, and decreases to 3.3 in market 4. These high levels of transaction activity indicate that the markets were active and that the observed episodes of mispricing are not a phenomenon associated with thin markets.

[8]To avoid rescaling of the figures, the prices of some periods in market 1 of sessions P2 and

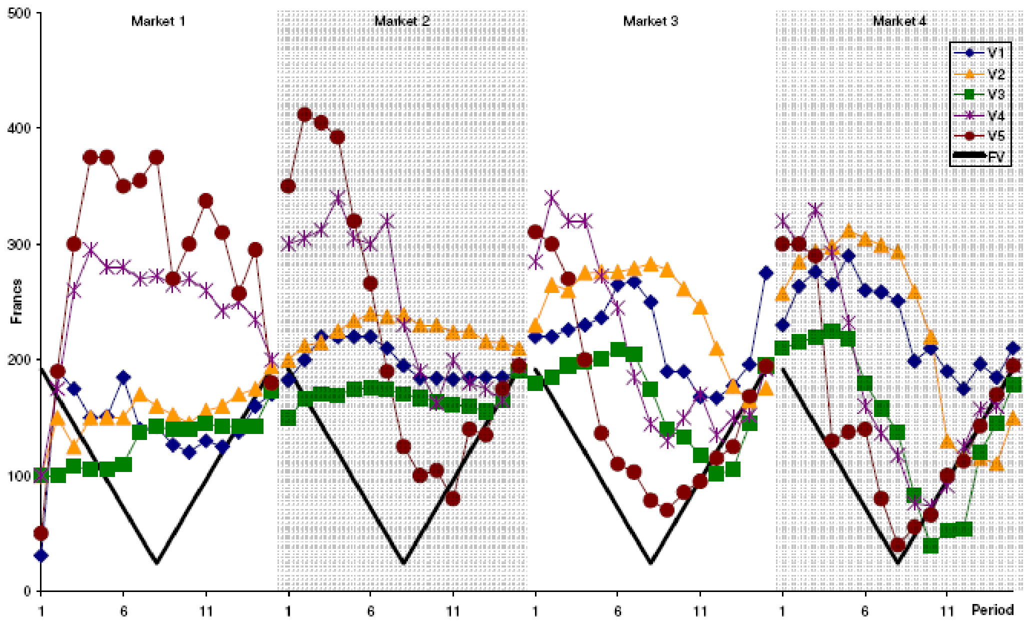
damentals closely in four of the five *Peak* sessions. In the *Valley* treatment, shown in the second panel of Figure 3.2, prices begin substantially below fundamental value in market 1. The prices then typically exhibit booms relative to fundamentals, increasing to levels well above fundamentals by the middle of the market and remaining above fundamentals for the remainder of the market. In subsequent markets, prices exceed fundamentals throughout the life of the asset. Late in markets 3 and 4, prices tend to crash to near fundamentals, which they then track for the remainder of the market. However, in those markets of the *Valley* treatment exhibiting a price trough and rebound, the time of the turnaround in prices is typically later than the turning point of fundamentals. Overall, the figures suggest that prices track fundamental values better in the *Peak* than in the *Valley* treatment. Result 3.1 reports the findings of the analysis comparing price level discovery in the two treatments.

P4 are not shown. These prices are 600, 800, and 600 in periods 7 - 9 of market 1 of P2, and 800, 750, and 700 in periods 8 - 10 of market 1 of P4.

Figure 3.2: Period Prices Relative to Fundamentals



(a) Peak Sessions



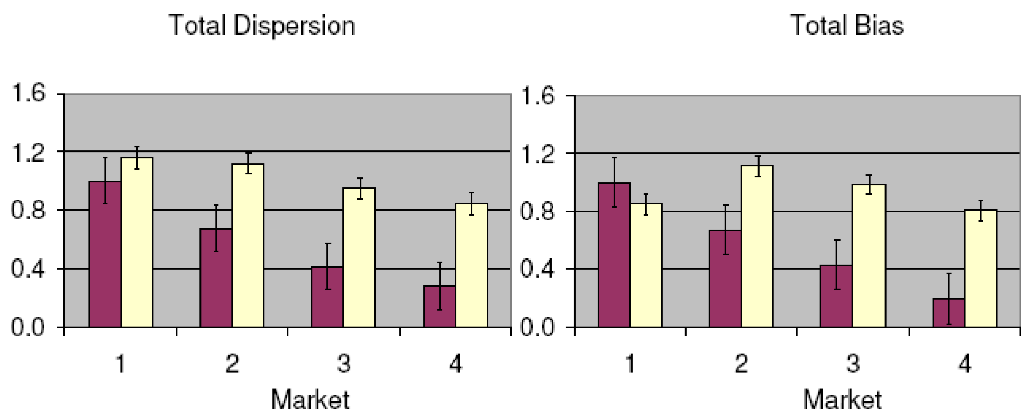
(b) Valley sessions

Result 3.1 *Price levels in* Peak *sessions are closer to fundamentals than they are in* Valley *sessions. That is, price level discovery is better in the* Peak *than in the* Valley *treatment. Hypothesis 1 is rejected.*

Support for Result 3.1 Figure 3.3 displays the observed values of *Dispersion* and *Bias* in the two treatments, averaged across the five sessions within each treatment[9]. Recall that values of *Dispersion* as well as *Bias* closer to zero indicate better price level discovery.

The results show that mispricing in *Valley*s is consistently greater than in *Peak*s by markets 3 and 4.

Figure 3.3: Measures of Price Level Discovery



Notes: Peak (dark bars) and Valley (light bars), averaged over sessions and relative to Peak-Market 1.

Table 3.2 indicates the results of two-sided rank-sum tests of differences in *Dispersion* and *Bias* between the two treatments. The test is conducted separately for the data from each of the four markets, which correspond to four different trader experience levels. Each session is used as the unit of observation, so that there are five observations from each treatment for each market. The columns indicate the mispricing measure under consideration. The rows correspond to the market(s) used for the comparison. The table shows that the hypothesis of equality between the two treatments can be rejected at the 5% level for both measures in favor of the alternative that they come from different distributions. Neither of the measures is significantly different between treatments if only the data from markets 1 or 2 is considered.

[9]The values of each measure for each market in each session of the *Peak* and *Valley* treatments are given in Table 3.6 in Appendix 3.A. The table also reports the values of trend and turning point discovery for each market and session. Table 3.8 in Appendix 3.A contains the results from an analysis of treatment differences using several other measures of price deviation from fundamental value that have appeared in the experimental literature (see King et al. (1993), Boening et al. (1993), or Porter and Smith (1995).

Table 3.2: Significance Levels of Treatment Differences

Market	Dispersion	Bias	Trend Discovery	Turning Point
1	0.347	0.465	0.008	0.086
2	0.175	0.175	0.035	0.287
3	0.047	0.047	0.245	0.595
4	0.028	0.028	0.090	0.034

Notes: Rank-sum tests of treatment differences in price discovery measures. Reported value is the significance level at which the hypothesis of equal distributions across treatments can be rejected. $N = 10$.

Next, the analysis turns to trend discovery, the measure of how consistently price changes from one period to the next are in the same direction as movements in fundamental values. Trend discovery is found to be better in *Peak* than in *Valley* treatments, for both markets with inexperienced and markets with experienced participants.

Result 3.2 *Price trends more accurately reflect underlying trends in fundamentals in* Peak *than in* Valley *markets. Hypothesis 2 is rejected.*

Support for Result 3.2 : Table 3.3 shows the fraction of periods in which prices and fundamentals move in the same direction, in each treatment and for each market. The first row of data, labeled *Peak* Treatment, shows the percentage of periods in the *Peak* treatment, in which prices and fundamentals move in the same direction. The next two rows indicate the similar percentage, for the subset of periods in which fundamentals are increasing (row 2) and decreasing (row 3) separately. The next three rows display the analogous data for the *Valley* treatment. The first four columns display the data for each market separately, and the fifth column contains the pooled data for all markets.
Table 3.3 shows that in over three quarters of periods in the *Peak* treatment, prices move in the same direction as fundamentals. In market 1 this percentage is 81.4%, and after decreasing somewhat in market 2, recovers to 82.9% in market 4. *Peak* market prices are especially likely to follow the same trend as fundamentals when fundamentals are decreasing (90.7% of periods) in the later periods of the markets. In the *Valley* treatment, price movements are in the same direction as fundamental changes in fewer than half of the periods in markets one and two, and reach a level of consistency of greater than 60%

Table 3.3: Price Trend Discovery

Treatment	Periods	Market(s) 1	2	3	4	All
Peak	all	.814	.729	.757	.829	.782
	$f_t > f_{t-1}$	.686	.571	.629	.743	.657
	$f_t < f_{t-1}$	.943	.886	.886	.914	.907
Valley	all	.400	.414	.514	.629	.489
	$f_t > f_{t-1}$	.515	.364	.545	.636	.515
	$f_t < f_{t-1}$	.297	.459	.486	.622	.466
all	all	.607	.571	.636	.729	.636

only by market 4. Overall, in the *Valley* treatment, prices move in the same direction as fundamentals 49.8% of the time, a percentage similar to one that would be obtained by assuming that price movements were independent of underlying fundamentals. No systematic difference in the level of consistency between price and fundamental value trends is observed between periods in which fundamentals are increasing versus when they are decreasing. Table 1 indicates the results of the test of the hypothesis that the distribution of Trend Discovery is the same across treatments (as indicated previously, each session is used as the unit of observation). The hypothesis is rejected in markets 1 and 2 at the 5% level, and in market 4 at the 10% level.

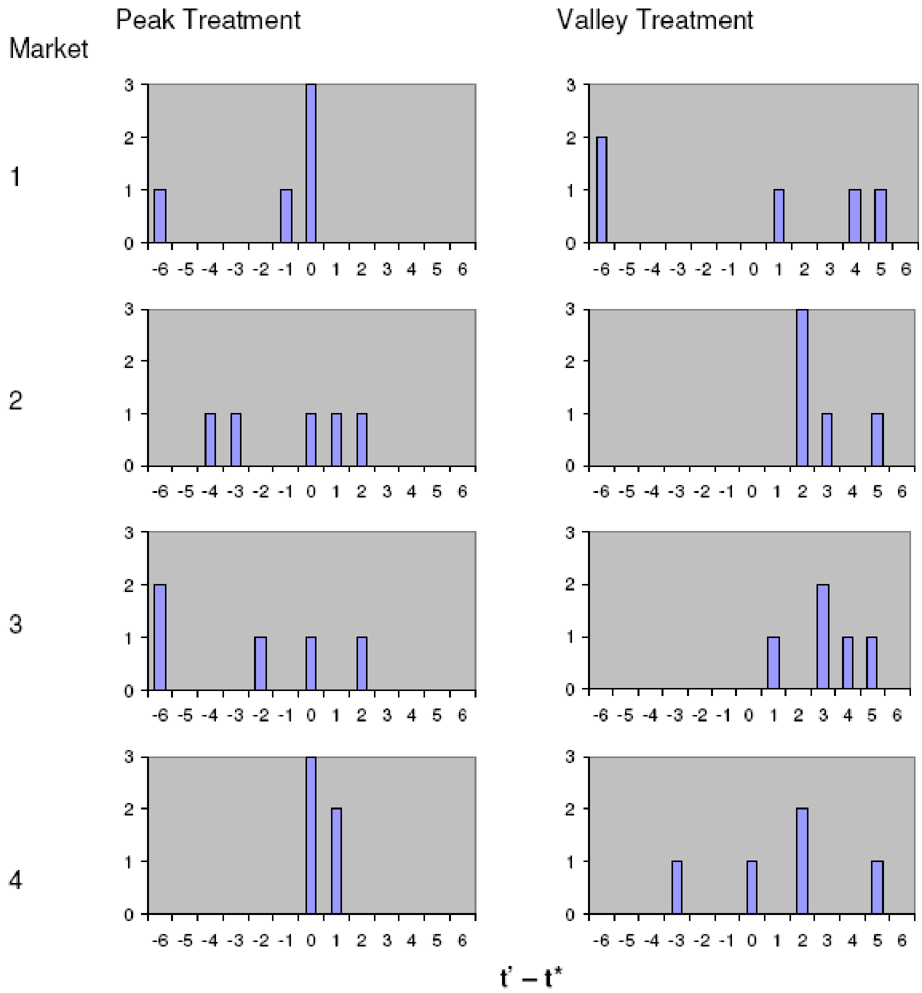
Attention now turns to turning point discovery, the relationship between the timing of the turning point of fundamentals and the turning point in prices. The observations are summarized below as Result 3.3.

Result 3.3 *Turning point discovery is better in the* Peak *than in the* Valley *treatment. Hypothesis 3.3 is rejected. By market 4 in the* Peak *treatment, the average turning point of prices in the* Peak *treatment is very close to that of fundamentals. In the* Valley *treatment, the turning point of prices is consistently later than that of fundamentals.*

Support for Result 3.3 : Figure 3.4 shows the difference between the turning points in prices and in fundamentals by market in each session. Positive values on the horizontal axis indicate that prices change direction later than fundamentals. The vertical axis indicates the number of sessions (out of a total of five) that the difference between the two turning points equals the value of the horizontal axis for the market shown in the panel. The turning points of prices are on average earlier than those for fundamentals in the *Peak* treatment in markets 1 - 3, but the difference is close to zero by market 4. The average turning point of prices in *Valley* is close to that of fundamentals in market 1, although all but one of the actual turning points of prices is at least 4 periods away from the turning point of fundamentals. However, in *Valley*, after the first market, price turning points are consistently later than those of fundamentals, and later than those in the *Peak* treatment.

The fourth column of data in table 4 contains the significance levels of rank-sum tests of the hypothesis that the distribution of turning point discovery is equal between the two treatments. The tests show that in market 4, the hypothesis of equality is rejected at the 5% level. The hypothesis is rejected at the 10% level for market 1.

Figure 3.4: Turning Point Differences



The patterns regarding the effect of experience on price discovery are summarized as Result 3.4.

Result 3.4 *Price level discovery improves with repetition in the* Peak *but not in the* Valley *treatment.*

Support for Result 4 Figure 3.3 shows the evolution of price level discovery in the markets as they are repeated and traders gain experience. In the *Peak* treatment, there is a tendency for market mispricing to decrease with repetition and thus for price level discovery to improve. In the *Peak* treatment, each measure of mispricing has an average value in market 4 that is less than 1/3 of the value in market 1. However, in the *Valley* treatment, dispersion is only on average 30% lower in market 4 than in market 1, and bias is a mere 2%

lower. While the measures are comparable in magnitude in market 1, by the final market dispersion is more than three time and bias more than four times greater in *Valley* than in *Peak*.

Comparing the treatments with regard to changes in trend and turning point discoveries with repetition yields a mixed picture. While improvement in the Trend Discovery between markets 1 and 4 is more rapid in the *Valley* treatment in percentage terms, the decrease in turning point discovery is greater in percentage terms in *Peak* than in *Valley*. However, both begin from a much more inefficient base in market 1 in the *Valley* than in the *Peak* treatment. Tables 3.3 and 3.6 indicate that the average trend discovery increases from .814 to .829 in *Peak*, and from .4 to .621 in *Valley*. Figure 4 shows that the average turning point discovery improves from 1.4 in market 1 to 0.4 in market 4 for the *Peak* treatment. It also decreases from 4.4 in market 1 to 2.4 in market 4 of the *Valley* treatment.

Table 3.4 reports the results of the following two types of statistical tests. The first type is a sign test that considers whether a mispricing measure is improving (decreasing for dispersion, bias, and turning point discovery, increasing for trend discovery) between consecutive markets within the same session. The test is conducted for each of the two treatments separately. For this test, there are fifteen observations in each treatment (5 sessions * (4 - 1) consecutive market pairs per session). The hypothesis and the resulting significance level of the sign test are reported in the first two rows of data in the table. The second type of test, reported in the final row of Table 3.4, is a rank-sum test of whether the distribution of percentage changes in a measure of mispricing from one market to the next is significantly different between the two treatments.

The first two rows of data in the table indicate the levels of significance at which the null hypotheses that the value of a mispricing measure is the same or deteriorating between market $m-1$ and m within the sessions can be rejected. The first row shows that for the *Peak* treatment, the null hypothesis is rejected for both dispersion and bias at the 5% level. For *Valley*, the same hypotheses cannot be rejected, indicating that there is no significant decrease in the values of these measures with repetition. The hypothesis, for the *Valley* data, that trend discovery is constant or decreasing from one market to the next is not rejected in favor of the hypothesis that it is increasing. However, recall that the trend discovery measures in the *Valley* treatment in markets one and two are less than 50%, the value that would result if price movements were purely random, so the improvement occurs from a very low base.

Table 3.4: Significance Levels of Differences in Price Discovery Changes Between Markets

Hypothesis	Dispersion	Bias	Trend Discovery	Turning Point Discovery	N
1	0.0037	0.0176	0.5000	0.2539	15
2	0.5000	0.5000	0.0461	0.1334	15
3	0.0095	0.0238	0.1965	0.0686	30

Notes: p-values that the hypotheses cannot be rejected are reported. Hypotheses 1 & 2 are that there is no difference in a given price discovery measure between consecutive markets in the Peak and Valley treatments, respectively. Hypothesis 3 is that the difference is equal in the two treatments.

The last row of the table indicates the significance level of a rank-sum test of the hypothesis that the magnitude of percentage changes in a mispricing measure from one market to the next is equal between the two treatments. Significant values indicate rejection of the hypothesis of equality. The data show that the improvement in price level discovery is significantly different between *Peak* and *Valley* by both measures at $p < 0.025$. The improvement is also greater for turning point inefficiency at the $p < 0.1$ level of significance.

In sessions 2 and 4 of the *Peak* treatment, an interesting pattern can be seen in Figure 3.2. In market 1 of these two sessions, large bubbles are observed in roughly the middle third of the life of the asset. In market 2, prices rise to relatively high levels early in the life of the asset, suggesting speculation on an impending repetition of the pattern of the previous market. Individuals demand more of the asset, pushing up prices, based on the belief that prices will follow a similar trajectory as in the prior market. Afterward, prices begin to decline before the period of peak prices in the preceding market, suggesting that individuals anticipate a peak to occur at roughly the same time in market 2 as has previously occurred in market 1, and supply units to the market before the time at which they anticipate a decline in prices. Thus, the dynamic pattern from one market to the next is consistent with the idea that the change in the price trajectory from one market to the next within a session reflects (a) expectations of a repetition of the price time series that occurred in the prior market, in conjunction with (b) the use of profitable strategies given those expectations[10].

[10] Haruvy et al. (2007) have suggested that a similar dynamic is at work for markets with declining fundamental values.

To explore whether this backward propagation of prices is a feature of the overall data, a test for whether changes in prices in period t between one market to the next can be explained by the difference between the previous market's prices in period $t+1$ relative to period t is conducted. Consider the following regression specifications:

$$\Delta_m p_{m,t} = \alpha_1 + \beta_1 \Delta_t p_{m-1,t+1} + \epsilon^1_{m,t} \quad (3.2)$$

$$\Delta_m p_{m,t} = \alpha_2 + \beta_2 \Delta_t bias_{m-1,t+1} + \epsilon^2_{m,t} \quad (3.3)$$

Here, $p_{m,t}$ is the price in period t of market m (indices for session are suppressed for expositional clarity).

The rationale for this specification is the following. Suppose a trader believes that prices in the current market will be the same as those in the previous market. Then, if prices in the prior market $m-1$ increased between periods t and $t+1$ ($p_{m-1,t+1} > p_{m-1,t}$), the trader's demand in period t of market m increases in anticipation of the price increase in the next period. This behavior causes prices to increase in period t of the current market m relative to the price in period t in the prior market $m-1$. An analogous effect would occur for price decreases. A positive β_1 would reveal this effect: it captures how much the change in price between periods t and $t+1$ in the previous market affects the period t price in the current market. Equation 3.2 considers the effect for absolute price levels and 3.3 for deviations of prices from fundamentals[11].

The results of the regression, presented in Table 3.5, suggest that behavior is consistent with a certain amount of response to beliefs that previous price patterns will be repeated. For the *Peak* treatment, the β coefficients are positive and significant under both specifications, and have values of 0.59 and 0.63 in equations 3.2 and 3.3, respectively. For the *Valley* treatments the β coefficients are also positive and significant, with larger values than in the *Peak* treatment, indicating that the backward propagation of prices is even stronger in the *Valley* sessions.

3.5 Conclusion

The experimental markets constructed here are used to obtain the first empirical observations, from a controlled laboratory study, of the behavior of asset

[11] Note that the dependent variable in Equation 3.3, $\Delta_m p_{m,t}$, is also equal to the difference between markets $m-1$ and m in terms of period bias, since f_t is the same in all markets.

Table 3.5: Change in Prices Between Sequential Markets as a Function of Activity in Prior Market

	Treatment			
Variable	*Peak*	*Valley*	*Peak*	*Valley*
constant	-17.11*	-1.72	-16.87*	-3.15
	(6.68)	(8.31)	(6.72)	(5.87)
$\Delta_t p_{m-1,t+1}$	0.59**	1.18**		
	(0.10)	(0.11)		
$\Delta_t bias_{m-1,t+1}$			0.63**	1.09**
			(0.10)	(0.09)

Notes: Standard errors in parentheses. $N = 210$.

markets that experience a peak or a trough in fundamentals. The analysis focuses on how well the market tracks the fundamental value, how well it reflects trends in fundamentals, and how well it reveals the timing of a change in trend. An additionaly consideration is how these measures of pricing accuracy evolve and improve as traders gain more experience through repetition of the market. The results are not obvious a priori in light of the strong tendency of experimental asset markets to generate bubbles and crashes when traders are inexperienced, a result that nonetheless has only been established for assets with fundamental values that are monotonically decreasing or constant over time.

Mispricing relative to fundamental values is typically observed in these markets populated with inexperienced subjects. As individuals gain experience, prices move much closer to fundamental values in the *Peak* treatment, in a manner similar to that observed in previous studies of experimental markets with declining fundamental values. However, in the time frame under consideration here, four repetitions of a 15-period market, the *Valley* treatment does not move appreciably closer to fundamentals. Price changes from one period to the next are typically in the same direction as the change in fundamentals in the *Peak* treatment, but not in the *Valley* treatment. The observed peaks and troughs in prices accurately reflect the timing of the turnaround in fundamental values in *Peak*, but are systematically too late in *Valley*.

Thus, a pronounced difference is found between the speed and the strength of the price discovery process in a market when the underlying fundamentals rise to a peak and then decline, and in a market where the fundamentals decline to a trough and experience a subsequent increase. In the *Peak* treatment, while the markets experience bubbles and crashes when traders are inexperienced, the markets operate at close to fundamentals after participants have acquired experience in the environment. On the other hand, a trough in fundamentals appears to represent a more challenging environment for the market to achieve accurate pricing. Prices consistently fail to reflect the level, the direction of the trend, and the timing of the turnaround, of fundamentals in the *Valley* treatment. The *Valley* treatment appears to be the first experimental environment in which asset markets populated by individuals with this level of experience with a stationary environment do not track fundamental values closely.

There is considerable debate in the economics profession about the extent to which markets produce prices that reflect underlying fundamental values. The evidence obtained here suggests that the answer may be that it depends on the properties of the process underlying fundamental values and the dynamics the process exhibits over time. We identify a strong asymmetry between how asset markets respond to peaks and troughs in fundamentals. This occurs even though the treatments are constructed to be similar in terms of level of complexity, monetary stakes involved, institutional structure, and in the characteristics of the individuals participating. Indeed, there may also be characteristics of the time path of fundamentals, other than whether they exhibit peaks and troughs, that enhance or impede the ability of a market to track fundamentals. The research presented in this chapter indicates that characteristics of the fundamental value, in addition to the well-known influences of the institutional structure and the level of sophistication of traders, are determinants of price discovery. While this is clearly a property of the laboratory markets under study here, it may also be a feature of markets outside the laboratory. If so, it suggests a conjecture that the tendency of markets to conform more closely to some trajectories of fundamentals than others might potentially reconcile differing conclusions on the extent to which asset markets display price discovery.

3.A Appendix

The first table presents the values of the four measures of price discovery (Dispersion, Bias, Trend Discovery, and Turning Point Discovery) in each market of each session. The table also includes averages and standard deviations across sessions within each treatment.

The second table, 3.7, shows the values for several measures of market deviation from fundamentals that previous authors (Haruvy and Noussair (2006), King et al. (1993), Porter and Smith (1995)) have employed. These measures are:

(1) $Amplitude = max_t(bias_t/f_t)/min_t(bias_t/f_t)$, where p_t and f_t equal the median transaction price and fundamental value in period t, respectively.

(2) $NormalizedDeviation = \sum_i |p_i - f_i|/TSU$, where p_i is the price of transaction i and f_i is the fundamental value of the share at the time that transaction i is executed. TSU is the total stock of units that agents hold.

(3) $Turnover = \sum_t q_t/TSU$, where q_t is the quantity of units of the asset exchanged in period t.

(4) $BoomDuration =$ the greatest number of consecutive periods for which $p_t > f_t$.

(5) $BustDuration =$ the greatest number of consecutive periods for which $p_t < f_t$.

In the table, the measures are reported for each market within each session, averaged across sessions for each treatment, and between session standard deviations.

Table 3.6: Measures of Price Discovery

	Mkt	P1	P2	P3	P4	P5	AvgP	(s.d.)	V1	V2	V3	V4	V5	AvgV	(s.d.)
Average Bias	1	8.70	179.6	20.7	148.4	27.2	76.9	(80.5)	3.0	14.6	15.3	130.1	174.4	67.5	(79.1)
	2	32.37	74.57	18.17	119.1	17.2	52.3	(44.0)	58.3	84.3	54.0	131.7	112.4	88.1	(33.8)
	3	22.43	23.6	15.0	93.0	1.8	31.2	(35.6)	79.4	104.6	52.1	99.1	43.9	75.8	(27.2)
	4	15.50	-5.87	-2.2	64.3	4.7	15.3	(28.6)	91.4	90.4	35.4	70.9	37.0	65.0	(27.6)
Total Dispersion	1	376	2697	489	2289	415	1253	(1142)	659	802	742	2135	2924	1452	(1024)
	2	520	1119	577	1787	258	852	(609)	1026	1352	908	1982	1736	1401	(457)
	3	369	500	439	1395	119	564	(486)	1231	1628	967	1519	708	1211	(381)
	4	276	260	221	965	74	359	(348)	1392	1623	938	1089	585	1125	(402)
1 - Trend Discovery	1	0.07	0.14	0.36	0.07	0.29	0.19	(0.1)	0.43	0.43	0.71	0.71	0.71	0.60	(0.2)
	2	0.07	0.29	0.50	0.43	0.07	0.27	(0.2)	0.57	0.79	0.64	0.64	0.29	0.59	(0.2)
	3	0.14	0.29	0.36	0.36	0.07	0.24	(0.1)	0.64	0.79	0.64	0.29	0.07	0.49	(0.3)
	4	0.14	0.07	0.21	0.43	0.00	0.17	(0.2)	0.43	0.64	0.36	0.21	0.21	0.37	(0.2)
Turning Point Difference	1	0.00	0.00	6.00	0.00	1.00	1.4	(2.6)	8.00	8.00	7.00	7.00	7.00	7.4	(0.5)
	2	1.00	3.00	7.00	4.00	0.00	3.0	(2.7)	8.00	8.00	7.00	2.00	3.00	5.6	(2.9)
	3	0.00	7.00	0.00	6.00	0.00	2.6	(3.6)	3.00	5.00	4.00	1.00	1.00	2.8	(1.8)
	4	1.00	0.00	0.00	0.00	0.00	0.2	(0.4)	3.00	5.00	2.00	2.00	0.00	2.4	(1.8)

Table 3.7: Additional Measures of Price Discovery

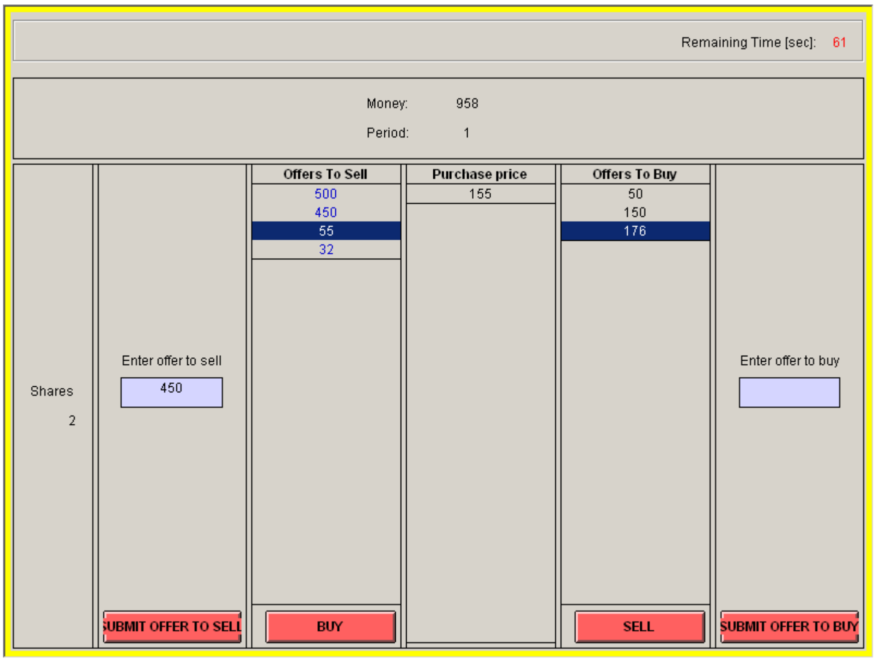
	Mkt	P1	P2	P3	P4	P5	AvgP	(s.d.)	V1	V2	V3	V4	V5	AvgV	(s.d.)
Amplitude	1	2.33	7.34	3.70	4.04	4.45	4.4	(1.8)	2.51	2.76	5.40	10.83	15.36	7.4	(5.6)
	2	4.46	9.39	5.51	9.38	2.83	6.3	(3.0)	3.07	3.96	6.30	8.60	4.38	5.3	(2.2)
	3	3.33	7.50	5.30	7.64	1.67	5.1	(2.6)	3.04	4.88	6.56	5.12	2.40	4.4	(1.7)
	4	2.92	2.51	2.40	7.25	0.28	3.1	(2.6)	3.19	4.74	5.28	3.95	1.10	3.7	(1.6)
Normalized Deviation	1	2.34	6.78	4.78	8.23	1.16	4.7	(3.0)	5.09	7.22	4.94	7.10	6.23	6.1	(1.1)
	2	1.91	2.81	1.80	6.79	0.72	2.8	(2.3)	5.99	5.98	3.36	4.07	3.04	4.5	(1.4)
	3	0.54	1.77	1.05	2.05	0.24	1.1	(0.8)	3.70	5.65	3.80	2.41	1.25	3.4	(1.7)
	4	0.64	1.08	0.26	1.97	0.09	0.8	(0.8)	2.61	4.09	2.67	1.49	1.10	2.4	(1.2)
Turnover	1	9.67	5.83	7.94	12.00	3.56	7.8	(3.3)	9.89	11.39	9.78	4.56	3.39	7.8	(3.6)
	2	4.28	2.78	3.39	3.78	3.11	3.5	(0.6)	8.06	7.11	5.50	2.78	2.83	5.3	(2.4)
	3	2.00	3.67	2.11	2.00	2.50	2.5	(0.7)	4.17	5.00	4.72	1.94	2.72	3.7	(1.3)
	4	2.17	4.22	1.44	3.39	1.67	2.6	(1.2)	2.83	4.17	4.06	2.33	3.11	3.3	(0.8)
Boom Duration	1	7.00	13.00	4.00	10.00	10.00	8.8	(3.4)	8.00	11.00	8.00	14.00	13.00	10.8	(2.8)
	2	7.00	15.00	5.00	15.00	7.00	9.8	(4.8)	12.00	13.00	11.00	13.00	10.00	11.8	(1.3)
	3	7.00	4.00	1.00	15.00	3.00	6.0	(5.5)	14.00	12.00	10.00	13.00	10.00	11.8	(1.8)
	4	5.00	4.00	3.00	15.00	4.00	6.2	(5.0)	14.00	11.00	9.00	10.00	9.00	10.6	(2.1)
Bust Duration	1	4.00	1.00	2.00	2.00	1.00	2.0	(1.2)	4.00	4.00	4.00	1.00	1.00	2.8	(1.6)
	2	2.00	0.00	5.00	0.00	0.00	1.4	(2.2)	2.00	2.00	2.00	1.00	1.00	1.6	(0.5)
	3	1.00	4.00	5.00	0.00	2.00	2.4	(2.1)	1.00	2.00	3.00	1.00	3.00	2.0	(1.0)
	4	2.00	5.00	9.00	0.00	1.00	3.4	(3.6)	1.00	4.00	6.00	1.00	2.00	2.8	(2.2)

Table 3.8: Tests of Treatment Differences

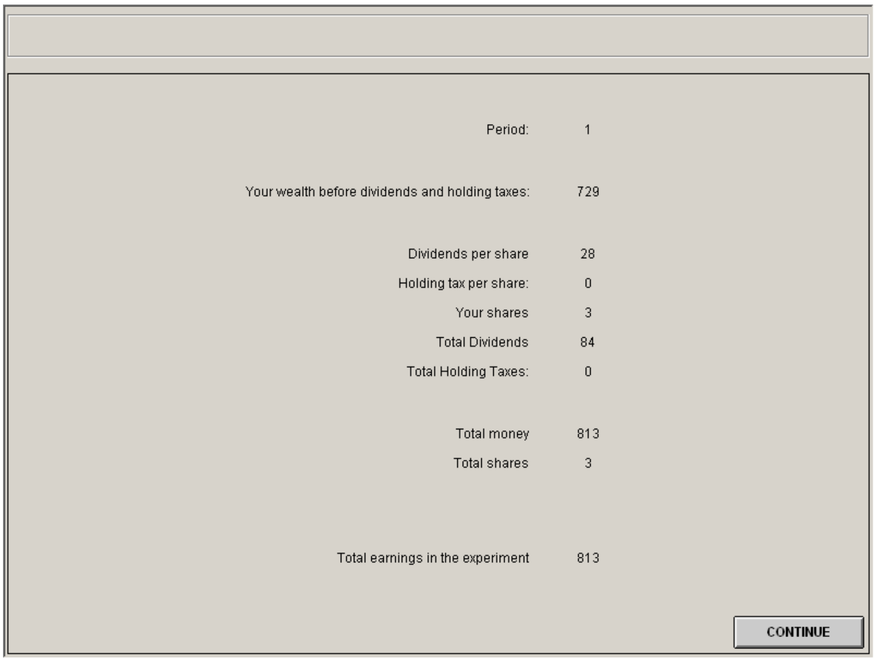
Market	Amplitude	Turnover	Boom Duration	Bust Duration	Normalized Deviation	N
1	0.465	0.917	0.248	0.502	0.347	10
2	0.465	0.402	0.600	0.381	0.117	10
3	0.465	0.173	0.092	0.827	0.028	10
4	0.347	0.347	0.112	0.747	0.028	10
All	0.788	0.330	0.868	0.194	0.065	30

Notes: Rank-sum tests of treatment differences in price discovery measures given in Table 3.7. Reported value in rows 1-4 are the significance levels at which the hypotheses of equal distributions across treatments can be rejected. Row 5 is the significance level at which the hypothesis of no treatment difference from one market to the next can be rejected.

Figure 3.5: Screenshots



(a) Trading Interface



(b) End-of-Period Information

Subject Instructions

Treatment-specific information is contained inside curly braces { } for the Peak treatment and square brackets [ ] for sessions V3-V5 of the Valley treatment (information for V1-V2 is omitted, as it is very similar to the information in V3-V5).

1. General Instructions

This is an experiment on decision making in a market. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money, which will be paid to you in cash at the end of the experiment. The experiment consists of a sequence of trading Periods in which you will have the opportunity to buy and sell in a market. The currency used in the market is francs. All trading will be done in terms of francs. The cash payment to you at the end of the experiment will be in Euros. The conversion rate is: 200 francs to 1 Euro.

2. How to use the computerized market

In the top right hand corner of the screen you see how much time is left in the current Period. The goods that can be bought and sold in the market are called Shares. In the center of your screen you see the current Period and the amount of Money you have available to buy Shares. To the left of the screen, you see the number of Shares you currently have. If you would like to offer to sell a share, use the text area entitled “Enter offer to sell:“ in the second column. In that text area you can enter the price at which you are offering to sell a share, and then select “Submit Offer To Sell”.

Please do so now. Type in a number in the appropriate space, and then click on the field labelled “Submit Offer To Sell”. You will notice that nine numbers, one submitted by each participant, now appear in the third column from the left, entitled “Offers To Sell”. The lowest ask price will always be on the bottom of that list and will, by default, be selected. You can select a different offer by clicking on it. If you select “Buy”, the button at the bottom of this column, you will buy one share for the currently selected sell price. Please purchase a share now by selecting “Buy”. Since each of you had offered to sell a share and attempted to buy a share, if all were successful, you all have the same number of shares you started out with. This is because you bought one share and sold one share.

When you buy a share, your Money decreases by the price of the purchase. When you sell a share, your Money increases by the price of the sale. You may make an offer to buy a unit by selecting "Submit offer to buy." Please do so now. Type a number in the text area "Enter offer to buy." Then press the red button labelled "Submit Offer To Buy". You can sell to the person who submitted the highest offer to buy if you click on "Sell". Please do so now. In the middle column, labelled "Transaction Prices", you can see the prices at which Shares have been bought and sold in this period.

You will now have 10 minutes to buy and sell shares. This is a practice period. Your actions in the practice period do not count toward your earnings and do not influence your position later in the experiment. The only goal of the practice period is to master the use of the interface. Please be sure that you have successfully submitted offers to buy and offers to sell. Also be sure that you have accepted buy and sell offers. You are free to ask questions during the practice period by raising your hand.

3. Specific Instructions for this Experiment

The experiment will consist of 15 trading periods. In each period, you are permitted to buy and sell shares. Shares are assets with a life of 15 periods. Your inventory of shares carries over from one period to the next. For example, if you have 5 shares at the end of period 1, you will have 5 shares at the beginning of period 2.

Dividends:

You may receive dividends for each share in your inventory at the end of each of the 15 trading periods. At the end of each trading period, including period 15, the experimenter will roll a sixsided die. The outcome of the roll will determine the dividend for the period. Each period, each share you hold at the end of the period earns you a dividend of:

- 0 francs if the die reads 1
- 8 francs if the die reads 2
- 28 francs if the die reads 3
- 60 francs if the die reads 4

If the roll is a "5" or "6", the die is rolled again. Each of the numbers on the die is equally likely. This means that the average dividend is 24. We arrive at 24 by averaging the four equally likely dividends: 0, 8, 28, and 60. That is, we calculate (0 + 8 + 28 + 60)/4 = 24. The dividends you earn from shares you own are automatically added to your money balance after each period.

[After dividends and taxes have been paid out at the end of period 15, the experimenter will purchase back all the shares in the market for 216 francs each from their current owners. This buyout value will be added to any dividends received in period 15.]

Holding Taxes:

At the end of the {first} [last] eight periods, you must pay a holding tax of 48 francs for each share in your inventory. That is, a tax is paid at the end of {period 1, period 2, . . . , and period 8} [period 8, period 9, . . . , and period 15]. No tax is paid at the end of each of the {last} [first] seven periods ({period 8, period 9, . . . , and period 15} [period 1, period 2, . . . , and period 7]). The taxes you owe on shares are automatically subtracted from your money balance at the end of each of the first [last] eight periods.

4. Average Holding Value Table

You can use the AVERAGE HOLDING VALUE TABLE (attached at the end of this document) to help you make decisions. It calculates the average amount of dividends and holding taxes you will receive and pay if you keep a share until the end of the experiment. It also describes how to calculate how much in future dividends and holding taxes you give up on average when you sell a share at any time.

1. Current Period: the period during which the average holding value is being calculated. For example, in period 1, the numbers in the row corresponding to "Current Period 1" are in effect.

2. Number of Remaining Dividends: the number of times that a dividend can be received from the current period until the final period. That is, it indicates the number of die rolls remaining in the lifetime of the asset. It is calculated by taking the total number of periods, 15, subtracting the current period number, and adding 1, because the dividend is also paid in the current period.

3. Average Dividend: the average amount of each dividend. As we indicated earlier, the average dividend in each period is 24 francs per share[, except for the last period, which has an average dividend of 24 + 216 = 240 francs].

4. Average Remaining Dividends: the average value of all the dividends you will receive for each share you hold from now until the end of the experiment. It is calculated by multiplying Number of Remaining Dividends by Average Dividend.

5. Number of Remaining Tax Payments: the number of times that a tax must be paid on a share from the current period until the end of the experiment. It is calculated by taking the total number of tax periods, 8, and subtracting the number of tax periods that have already passed.

6. Tax Amount: the amount that the tax payment per share will be. As indicated earlier, there is no tax in the {last} [first] 7 periods, while the tax amount is 48 francs per share in the {first} [last] 8 periods.

7. Remaining Taxes: the total value of the taxes remaining on a share from now until the end of the experiment. That is, for each unit you hold in your inventory for the remainder of the experiment, you will pay the amount listed in column 7 in holding taxes. It is calculated by multiplying Number of Remaining Tax Payments by Tax Amount.

8. Average Holding Value: the average value of holding a share for the remainder of the experiment. That is, for each unit you hold in your inventory for the remainder of the experiment, the difference between the dividends you earn and the taxes you pay will on average be the amount listed here. It is calculated by subtracting Remaining Taxes from Average Remaining Dividends.

Please have a look at this table now and make sure you understand it. Feel free to raise your hand if you have a question. When you feel comfortable with it, please go on and answer the following practice quiz:

PRACTICE QUIZ

1. Suppose it is period 10. How much will you pay in taxes on a share if you hold it for the remainder of the experiment?

ANSWER:

2. Suppose it is period 10. How much do you expect to receive in dividends on a share if you hold it for the remainder of the experiment?

ANSWER:

3. Suppose it is period 10. What is the average value of holding a share for the remainder of the experiment?

ANSWER:

5. Your Earnings

Your earnings for the experiment will equal the total amount of money that you have at the end. More specifically, your earnings will be:

the money you begin with + any dividends you receive - any taxes you pay + any money you receive from sales of shares - any money you spend on purchases of shares.

6. Beginning the experiment - From now on your decisions will count toward your earnings, so please think carefully before making them.

received in the previous period.

Table 3.9: Average Holding Value (V3-V5)

Current Period (1)	Number of Remaining Dividends (2)	Average Dividend (3)	Average Remaining Dividends (4)	Number of Remaining Tax Payments (5)	Tax Amount (6)	Remaining Taxes (7)	Average Holding Value (8)
1	15	24	576	8	0	384	192
2	14	24	552	8	0	384	168
3	13	24	528	8	0	384	144
4	12	24	504	8	0	384	120
5	11	24	480	8	0	384	96
6	10	24	456	8	0	384	72
7	9	24	432	8	0	384	48
8	8	24	408	8	48	384	24
9	7	24	384	7	48	336	48
10	6	24	360	6	48	288	72
11	5	24	336	5	48	240	96
12	4	24	312	4	48	192	120
13	3	24	288	3	48	144	144
14	2	24	264	2	48	96	168
15	1	$24 + 216$	240	1	48	48	192

CHAPTER 4

FIRM INTERVENTIONS: SHARE ISSUES AND SHARE REPURCHASES [1]

This chapter looks at share repurchases and share issues in bubble markets. Although the intrinsic value of the shares is independent of the quantity outstanding, the interventions result in changes in asset price. The findings are that: (1) A repurchase of shares increases the price of the asset, and a share issue decreases the price of the asset, compared to a benchmark of no intervention. The effects are consistent with the capital structure puzzle, a negative correlation that is typically observed between the price and the supply of shares of stock. (2) The empirical patterns observed are consistent with a model proposed by De Long et al. (1990), which posits three trader types– fundamental, speculator, and momentum– interacting in the market. (3) The downward pressure on prices resulting from share issues drives prices down toward, but not beyond, fundamental values. This downward resistance at the fundamental value appears to arise from the impact of an intervention on the proportion of the total stock of units and cash held by each trader type.

4.1 Introduction

There is considerable evidence that market interventions in the form of share issues or repurchases can affect asset prices. On average, the price of a stock

[1] This chapter is based on Haruvy et al. (2010).

falls after a firm announces a share issue (Grinblatt and Hwang (1989); Ritter (1991); Loughran and Ritter (1995); Spiess and Affleck-Graves (1995))[2], while repurchase announcements are typically followed by increases in share prices (Masulis (1980); Vermaelen (1981); Bartov (1991); Grullon and Michaely (2004); Lie (2005))[3]. This phenomenon is referred to as the capital structure puzzle (Stigler (1964); Myers (1984)). However, such interventions are typically not exogenous, and the resulting price changes can usually be explained by the claim that the interventions either affect the fundamental value of the stock, or influence investors' beliefs about fundamentals. This would be the case, for example, if the choice to intervene was indicative of capital structure optimization, signaling, insider knowledge or executive compensation schemes (Mintz (1987); Lowenstein (1991); Bagnoli et al. (1989); Dittmar (2000); Brav et al. (2005); Bhattacharya (1979); Miller and Rock (1985); Vermaelen (1981), Vermaelen (1984)).

On the other hand, it has been proposed that changes in the supply of shares can affect stock prices solely because some traders value the shares more than others. Thus, the greater is the supply of shares; the lower is the valuation of the marginal shareholder. This would be the case even in settings, in which the quantity of shares does not affect their fundamental value. There is evidence consistent with this notion. Shleifer (1986) finds that stocks trade at higher prices in the first ten days after their inclusion in the S&P500 than in the next ten days, suggesting that buyers with higher valuations purchase the stock first and others with lower valuations follow. Similar conclusions have been reached by other authors (Scholes (1972), Mikkelson and Partch (1985), Kaul et al. (2000), Wurgler and Zhuravskaya (2002), Lynch and Mendenhall (1997)), who all interpret their results as consistent with the existence of a portion of investors who have higher marginal values than others. If this is

[2]A particularly striking recent example of this phenomenon is the recent US government takeover of Fannie Mae and Freddie Mac in September 2008. The companies faced an urgent need for liquidity to meet short term debt obligations, and attempted to float a large number of new shares. However, the act of doing so had such a large negative effect on prices that the firms' market capitalization fell dramatically. This exacerbated their liquidity crisis and precipitated the nationalization of the two companies.

[3]Typically, there is a spike in share price immediately following the repurchase announcement (Masulis (1980)). However, Lie (2005) finds that firms that merely announce a repurchase program without actually repurchasing shares are less likely to experience a subsequent performance improvement, whereas firms that follow through on their announcements continue to experience large performance improvements within two quarters, persisting for at least two years thereafter. Grullon and Michaely (2004) find increases only in the year of the announcement and not in subsequent years.

the case, share repurchases would increase, and share issues would decrease, prices, even if they do not affect fundamentals or beliefs.

In the research reported here, the experimental method is used to investigate how this latter effect might operate[4]. To do so, all of the factors that might allow a share repurchase or issue to affect the fundamental value are stripped away while the properties of the market response to an exogenous intervention are studied. The markets used here are for assets whose fundamental value is independent of the total supply of shares. The supply of shares of the asset then varies exogenously with share repurchases and share issues. While the repurchase or share issue has no effect on the intrinsic value of the asset[5], the intervention does affect the environment in ways that, coupled with boundedly rational trader behavior, may well change outcomes. A share issue or a repurchase changes the supply of shares relative to the cash available for purchases by traders[6]. In addition, it may change the allocation of shares among individuals, and thereby affect the weight or influence that traders of different types or using different strategies exert on market activity. These effects may lead the market to exhibit a price response to an intervention.

Three specific issues are considered. The first is whether repurchases and share issues affect price level in a setting in which they can have no impact on an asset's intrinsic value. The second is whether either of the interventions leads to pricing of the asset closer to its intrinsic value. The third is whether the price patterns are consistent with a particular theoretical model, proposed

[4]Experimentally, capital structure considerations have been investigated regarding investors' myopic attitudes to bond and stock payoff streams (e.g., Gneezy and Potters (1997); Eriksen and Kvaloy (2009)) as well as to differential ability of equity and debt auctions (for venture capital funding) to result in efficient outcomes in the presence of asymmetric private information (Kogan and Morgan (2009)). In this investigation, in contrast, a two-sided market trading of one asset class is studied, with information regarding fundamental values commonly known and the analysis focused on relative demand and supply effects in asset trading.

[5]Another way to introduce shares to the market in a revenue neutral manner is through a share split. A share split simply replaces each share held by investors with a fixed number of shares greater than one. The idea behind such a conversion is to increase share liquidity when individual share units are deemed too expensive for some investors. At least in principle, this action could relax constraints on purchases by cash- strapped traders in later stages of the experiments. Additional sessions, not reported here, and found that investors quickly made full adjustments for share splits.

[6]See Caginalp et al. (1998) for a discussion of the effect of varying cash levels on bubble magnitudes. They observe a $0.14 - 0.29$ correlation between price levels and the amount of cash per share, suggesting that prices increase by around 20 currency units for every 100 currency units per share added to the market.

by De Long et al. (1990) and applied to experimental data by Haruvy and Noussair (2006) (hereafter HN). In the model, each trader in the market is classified as belonging to one of three possible types. The three types are (1) fundamental value traders, who purchase and sell based on differences between price and fundamentals, (2) rational speculators, who anticipate and trade on future price movements, and (3) momentum traders, who trade as if they believe that previous price trends will continue.

Specifically, the fundamental value traders increase their holdings when prices are below fundamentals and decrease their holdings when prices are above fundamentals. Fundamental value traders thus behave like rational agents in classical models, who assume that the rationality of all traders is common knowledge. The momentum traders follow historical trends, increasing their holdings when prices have been increasing in the recent past and reducing them when prices have been declining. The rational speculator accumulates holdings before prices increase and reduces holdings before prices decrease, while ignoring the difference between prices and fundamentals. These traders are rational, have correct short-term expectations about future prices, and recognize that prices will not necessarily follow fundamentals. Rational speculators are similar to the rational arbitrageurs of Abreu and Brunnermeier (2003) (hereafter AB) in that they try to "ride" the bubble. However, the rational speculators have more accurate beliefs. Rational arbitrageurs in AB have diverse opinions (also see Morris (1996)) about the exact timing of the bubble and these differences result in a lack of synchronization and the persistence of the bubble. In contrast, rational speculators in the model presented here have identical and correct beliefs about future prices[7].

Three empirical patterns that emerge from the simulations serve as the hypotheses for the experiment. These are the following: (1) Repurchases increase prices, while share issues reduce prices. (2) Asset prices are closer to funda-

[7] A similar model with three trader types was applied to experimental data by Caginalp and Ilieva (2008) (hereafter CI). In the CI model, traders were classified into momentum traders, fundamental value traders, and neutral traders. The first two types correspond to the types of the same name discussed above. The neutral trader is essentially a catch-all category for those traders that could not be classified as the first two types. Rational speculators were not assigned a separate category. There are also two main implementation issues that differ between the HN and CI models. The first is that the HN classification looks at a trader's executed trades whereas CI classifies according to offers to buy and sell. The second is that HN classify a trader as belonging to the same type throughout the life of the asset, whereas CI allows a trader to switch type in each period. Each method comes with advantages and disadvantages but the HN classification permits simple simulations along the lines of De Long et al. (1990), and this is an important component of the research strategy used here.

mentals after a share issue, and they are farther away from fundamentals after a repurchase than they would have been in the absence of an intervention. (3) A repurchase reduces the fundamental value traders' proportion of the market power, as measured by an index weighting the proportion of the total stock of shares and cash they hold. In contrast, they have a higher proportion of the market power after a new share issue. In the simulations, the greater market power of fundamental value traders after a share issue appears to be the reason that prices track fundamentals more closely after a share issue.

The results of the experiment are presented in section 4.4. The three patterns described above are found to appear prominently in the data. (1) Prices are greater after a repurchase than after a share issue. (2) The absolute difference between prices and fundamentals is greater after a repurchase than after a share issue. (3) The interventions alter the weight that fundamental value traders have in the market. A repurchase reduces the market power of fundamental value types, while a share issue does the opposite. The greater weight that fundamental value traders have after a share issue appears to account for the strong tendency for prices to closely track fundamentals after the share issue. This conjecture is supported with additional simulations of interventions of different sizes in section 4.4.3.

4.2 Hypotheses

Consider a non-exhaustive classification of traders based on De Long et al. (1990) and applied to experimental data by Haruvy and Noussair (2006). The classification system consists of the following three types of traders:

1. Fundamental Value Traders (FV): These traders increase (decrease) share holdings when median price is below (above) fundamental value[8].
2. Momentum Traders (MM): These traders increase (decrease) share holdings in response to an upward (downward) price trend in the recent past.
3. Rational Speculators (RA): These traders correctly anticipate the next period's price movement. If the price move is upward (downward), they increase (decrease) holdings of shares.

The simulation model has the following features. The demand function of the *momentum traders* in period t is of the form $-\delta + \beta(p_{t-1} - p_{t-2})$, where p_t

[8]De Long et al. (1990) and Haruvy and Noussair (2006) referred to this type of trader as a Passive Trader. However, for clarity, the term *Fundamental Value trader (FV)* is employed here.

is the average transaction prices in periods t, and δ and β are parameters. The demand function of the *fundamental value traders* is $-\alpha(p_t - f_t)$. Finally, the *rational speculator*, who has demand given by $\gamma(E(p_{t+1}) - p_t)$, trades based on the difference between the expected price in the next period and the current spot price. It is assumed that speculators have correct expectations of the next period's price, and thus $E(p_{t+1}) = p_{t+1}$. The simulation thus has four demand parameters denoted by δ, β, α, and γ.

The simulations presented in Figures 4.1 and 4.2, which are used as the basis for the null hypotheses for the experiment, assume the parameter values and proportions of trader types estimated in Haruvy and Noussair (2006). The parameter values were estimated by minimizing the distance between the simulated price patterns and actual data in their experiment[9]. The values are $\alpha = 0.75$, $\beta = 0.13$, $\gamma = 0.55$, and $\delta = 0.48$. The proportions of trader types are 0.33, 0.42, and 0.25, for fundamental value, momentum and rational speculators respectively.

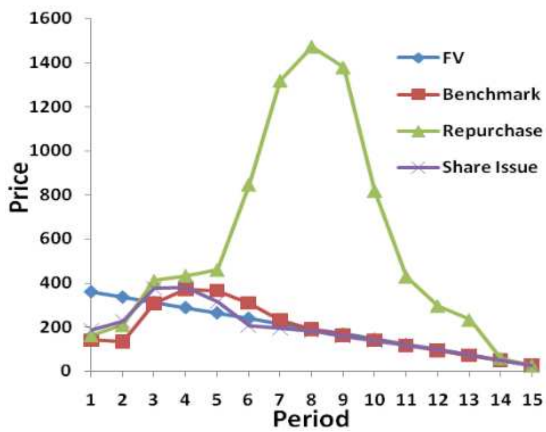
Each set of market simulations includes 150 repetitions, or 150 groups of nine simulated traders. Traders are drawn at random from the three types with a probability corresponding to their assumed proportions. Each trader begins period 1 with the initial endowment of money and shares allocated to him in the current experiment. Next, there is a grid search on prices in each period. Prices are determined by setting net demand equal to zero (equating demand and supply). The price is adjusted until the net excess demand equals zero. We solve for period prices one by one, proceeding sequentially. There are two iterations through the 15 periods to solve for prices. The first iteration determines the beliefs of the speculators; the second iteration solves for the actual prices. The figures show the average over the 150 simulated markets[10].

[9] Haruvy and Noussair (2006) assume that their markets are characterized by the interaction of the three types postulated by DeLong et al. (1990). They find that the model can explain the price patterns emerging from the relaxation of short selling constraints, as well as price patterns following the infusion of cash into the market. Specifically, they study conditions where traders could sell stocks short under different short-sale and cash reserve constraints. They also study conditions where cash in the system is multiplied by 10 over baseline levels. In general, loosening of short selling constraints lowers prices and increasing cash balances raises prices.

[10] Periods 1 and 2 are fixed at empirical values (the actual average values observed in the experimental treatment that is simulated). The price in period 15 is assumed to be 24, the period 15 fundamental value. These restrictions are necessary because the momentum types take prices in the two prior periods as exogenous and the rational speculator type takes the price one period ahead as exogenous.

Figure 4.1 shows the results of simulations of the market price patterns for the three treatments. The vertical axis indicates the price level and the horizontal axis the market period. The Benchmark treatment produces a bubble lasting from period 4 until period 7. The Share Issue treatment shows a decrease in price at the time of the intervention in period 6 to below fundamental values, but tracks fundamentals closely afterwards. The Repurchase treatment exhibits an acceleration of the bubble at the time of the intervention, and a market crash beginning in period 10. The figure shows that the model produces the price patterns associated with the Capital Structure Puzzle. A share issue lowers prices whereas a repurchase increases prices, compared to the levels at which they would have been in the absence of the intervention.

Figure 4.1: Simulation Prices



The first hypothesis is that share repurchases increase prices and share issues lower prices, relative to the Benchmark treatment.

Hypothesis 6 *Repurchases lead to higher prices, and share issues lead to lower prices, than would have existed in the absence of the intervention.*

Another pattern that appears in Figure 4.1 is that the treatments differ in how far prices diverge from fundamentals. The figure suggests that pricing is on average closer to fundamental values in the Share Issue treatment than in the Benchmark treatment, which is in turn closer than in the Repurchase treatment.

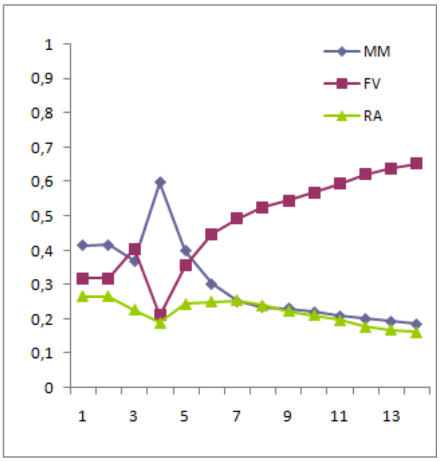
Hypothesis 7 *The share issue moves prices closer to fundamental value, while the repurchase moves prices farther away from fundamentals, then they would be in the absence of an intervention.*

The simulations suggest that in the Share Issue treatment, prices tend to track fundamental values fairly closely. Closer inspection of the allocation of cash and share inventories held by individuals of each type suggests that this pattern appears to be related to the fact that an intervention exerts an effect on the relative market influence of the three trader types. If a share issue shifts influence away from momentum traders and toward fundamental value traders, this provides a plausible account for the ability of the share issue to reduce mispricing. If the opposite effects occur after a share repurchase, that momentum traders gain influence and fundamental value traders lose influence, this would provide an account of how the share repurchase could exacerbate the bubble. Consider the following measure of the market power of subject i in period t:

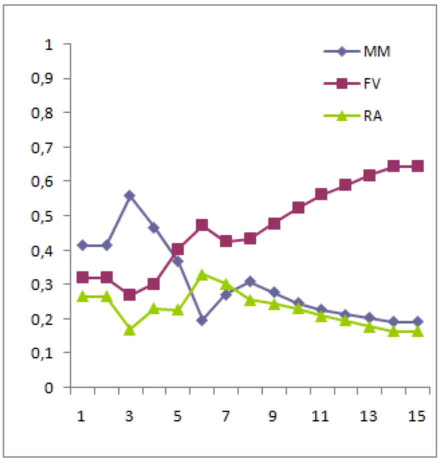
$$Power_{i,t} = 0.5\frac{s_{i,t}}{s_t} + 0.5\frac{c_{i,t}}{c_t},$$

where s_t and c_t indicate total shares and cash in period t, respectively. Each trader i begins each period t with inventories of shares $s_{i,t-1}$ and cash $c_{i,t-1}$. These inventories are also equal to the shares and cash that player i holds at the end of period $t-1$, after the dividend for period $t-1$ has been paid. The measure is a convex combination of subject i's relative share of the total cash and stock available in the period, with equal weight on each dimension. This measure is used to study whether differences in price paths between treatments can be explained by a reallocation of market influence among trader types as a consequence of an intervention.

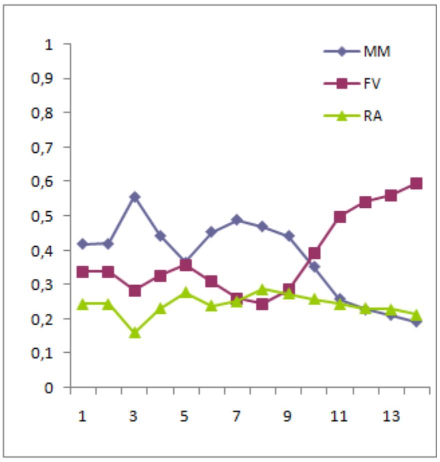
Figure 4.2: Simulated Market Power



(a) Benchmark



(b) Share Issue



(c) Share Repurchase

Figures 4.2a - c illustrate the evolution of market power of the three types of trader in each of the three sets of simulations. The vertical axis indicates the total market power of all agents of each type, and the horizontal axis is the market period. To understand the patterns, recall the dynamics of the typical bubble price pattern as displayed in Figure 4.1. Also bear in mind that purchases at low prices and sales at high prices increase a trader's relative market power.

In the early periods of each treatment, momentum traders tend to increase their market power as they purchase shares aggressively at low prices. In the Benchmark treatment, however, after a bubble forms, the MM traders make purchases from fundamental value traders at high prices, reducing their power, while increasing the power of FV traders. As prices fall and the market operates near fundamentals for the remainder of the life of the asset, FV traders steadily accumulate market power, since they only make trades that are profitable on average.

In the Repurchase treatment, the intervention increases the market power of MM traders and decreases that of FV traders as a large bubble forms. At the time of the intervention, the fundamental value traders quickly run out of shares and prices continue to rise in response to the demand generated by the repurchase. The momentum traders, however, hold out for higher prices and thus sell to the experimenter near the top of the bubble, increasing their market power. However, after the intervention is completed, the MM traders return to making unprofitable purchases at high prices, leading to a reduction in their market power.

Under a Share Issue, the intervention causes an increase in the market power of FV traders and a decrease in that of MMs. The intervention supplies new shares to the market, lowering the market price to a level below fundamentals. The FV traders purchase the bulk of these units, and do so at favorable prices. RA traders also purchase some of the units as they anticipate the subsequent increase in price to fundamentals, but MM traders miss out on the bargain. These shares generate cash dividends, so the fundamental value traders have large and increasing quantities of both cash and shares to keep the market from deviating too far from fundamentals for the remainder of the life of the asset. As the market operates close to fundamentals, FV traders steadily accumulate market power by receiving dividends and by taking advantage of small price fluctuations. Hypothesis 8 posits that in the experiment, the share of the market power of fundamental value traders will exhibit similar differences between treatments as in the simulations.

Hypothesis 8 *Over the life of the asset, the average market power of Fundamental Value traders is lowest under the Repurchase treatment. The Market Power of Fundamental Value traders is greatest under the Share Issue treatment.*

4.3 Experimental Design

The design consists of three treatments (based on the general design described in 2.4: a *Benchmark* treatment in which no external intervention takes place, a *Repurchase* treatment where a share repurchase occurs, and a *Share Issue* treatment where additional shares are sold into the market. In the Repurchase treatment, an intervention occurs at time t^* in which one half of $\sum s_{i,t*}$, the total stock of units that all traders hold, is purchased. In the Share Issue treatment, an intervention occurs at time t^* as well, when one half of $\sum s_{i,t*}$ additional shares are sold to traders. Thus the Repurchase and the Share Issue represent interventions of equal size.

The subjects know that an intervention will occur in some future period but do not know the period t^* in which this intervention will happen. Prior knowledge of t^* would have permitted coordination by subjects, thus fundamentally changing the nature of the market. For example, Abreu and Brunnermeier (2003) argue that news events at a defined future point make it possible for rational speculators to synchronize their exit strategies.

Table 4.1 provides a summary of the parameter choices for the experiment[11].

The implementation of the interventions operated as follows. In period t^*, an intervention occurred in the Share Issue and Repurchase treatments, but not in the Benchmark treatment. In the Share Issue (Repurchase) intervention, the computerized firm received a trading requirement that involved selling (buying) a certain number of shares to (from) the market. The computerized firm then participated in the market until its target had been achieved[12]. To achieve its target, the computerized firm periodically checked whether the bid-ask spread was above or below a certain threshold. If the bid-ask spread was above the threshold, the firm placed a new offer to sell (buy) for one unit that was lower (higher) than the current best standing offer to sell (buy) by the amount of some threshold. Otherwise the firm accepted the best standing offer to buy (sell). The parametric structure of the markets and interventions is summarized in Table 4.1.

4.4 Results

4.4.1 Price Patterns

The dataset consists of six sessions conducted under each treatment, for a total of 18 sessions[13]. Four sessions of each treatment were conducted at Tilburg

[11] These were identical to those used in Smith et al. (1988) for their "design 4" parameterization, but with initial endowments of shares of each individual doubled.

[12] This is similar in spirit to Veiga and Vorsatz (2009), who study the effects of a similar uninformed trading rule on price discovery.

[13] Two sessions only included 8 subjects. For these sessions one less subject was assigned as a Type 2 agent, so that on average the number of initial shares and cash per subject was the same across all sessions.

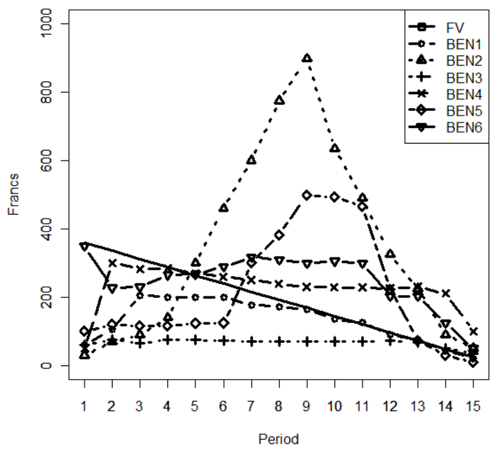
Table 4.1: Design Parameters

Parameter	Value
Period length	240 seconds
Initial portfolios	(shares, cash)
	(6, 450); (4, 1170); (2, 1890)
Exchange rate	170 francs = 1 Euro or
	150 francs = 1 US dollar.
Length of time between firm actions	5 seconds
Intervention size	50% of outstanding shares
Bid-ask spread threshold	10 francs
Time of intervention start, t*	Beginning of Period 6

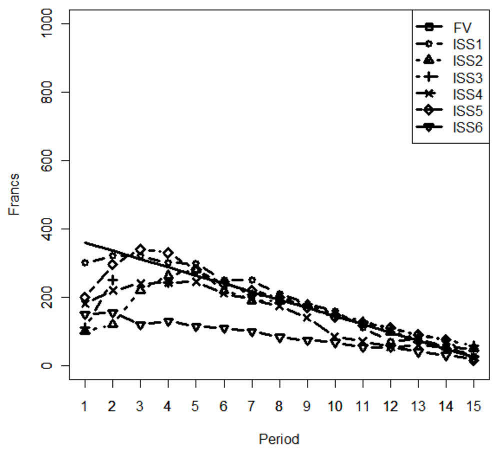
university, and two at the University of Texas at Dallas. Subjects were recruited via an online system and through posters and announcements. On average, the sessions lasted 2 hours.

Figure 4.3 illustrates the median transaction price by period in each session, along with the fundamental value. Each of panels (a)-(c) corresponds to one of the treatments. Within each panel, one time series represents the fundamental value and the others each represent prices in one session. Panel (d) presents the averages over the six sessions of each treatment.

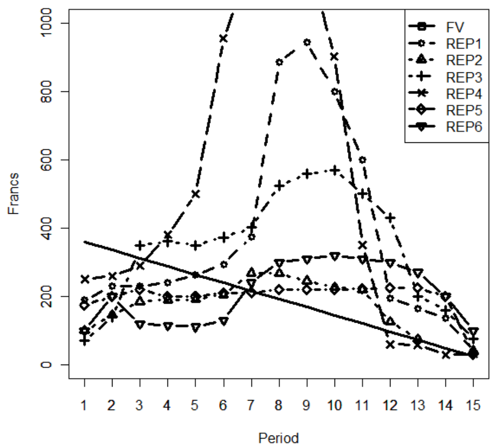
Figure 4.3: Period Prices Relative to Fundamentals



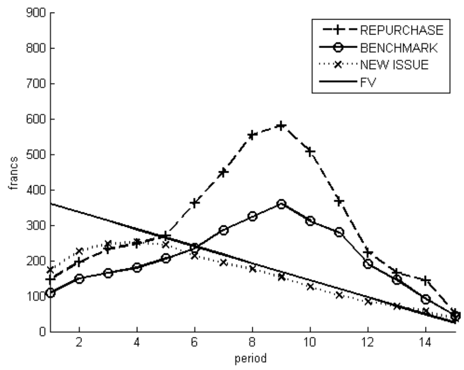
(a) Benchmark



(b) Issues



(c) Repurchases



(d) Treatment Averages

Notes: Treatment averages are the average over all sessions of a treatment. The prices in periods 7-9 of session R4 are 1200, 1130, and 1207.

We first consider whether Hypotheses 6 and 7 are supported. The figures above show that prices are higher in the Repurchase treatment than in the Benchmark treatment. In turn, they are higher in the Benchmark treatment than under Share Issue. Furthermore, in the Repurchase and Benchmark treatments, prices are substantially greater than fundamentals for most of the trading horizon. *Bias*, a measure of the overall price level, is used to formally test

Table 4.2: Treatment Averages of Mispricing Measures

Measure of Mispricing	Repurchase	Benchmark	Share Issue
Bias	1596	196	-519
Dispersion	2795	2032	698
Bias, periods 6 to 15	3102	1421	-165
Dispersion, periods 6 to 15	3228	1897	363

Table 4.3: Hypothesis test results: p-values

Hypothesis	Repurchase vs. Benchmark	Benchmark vs. Share Issue	Repurchase vs. Share Issue
H1, Bias	0.485	0.310	0.015**
H2, Dispersion	0.394	0.015**	0.009**
H3, Market Power of FV traders	0.643	0.114	0.049**

the hypothesis. Table 4.2 below indicates the Bias averaged over all sessions of each treatment, as well as the subset of periods 6 - 15 only, the time after which the intervention has taken place.

The p-values resulting from rank-sum tests of the hypotheses (taking each session in its entirety as an observation) are shown in Table 4.3. *Bias* is significantly different at the 5% level between the Repurchase and the Share Issue treatments (p-value=0.015), while neither of the two treatments is significantly different from the Benchmark treatment. The significance of the difference between prices under the two different interventions, coupled with the fact that all pair-wise treatment differences observed are in the direction predicted by the hypothesis (see Table 4.2, leads to the conclusion that the hypothesis is supported.

A similar pattern is observed in Table 4.3 with respect to aggregate mispricing as measured by Dispersion. The ranking of treatment averages follows the same pattern as it did for Bias. Specifically, Repurchase sessions have the highest magnitude of mispricing relative to fundamentals, followed by Benchmark, and then Share Issue. Table 4.3 reports that two of the three differences between treatments are highly significant ($p < 0.015$), providing strong sup-

Table 4.4: Criteria for classification of traders to types

Trader Type	Signal
Fundamental Value	$-bias_t$
Rational Trader	Δp_{t+1}
Momentum	Δp_{t-1}

Notes: The sign of the change in share holdings is the same as the signal sign.

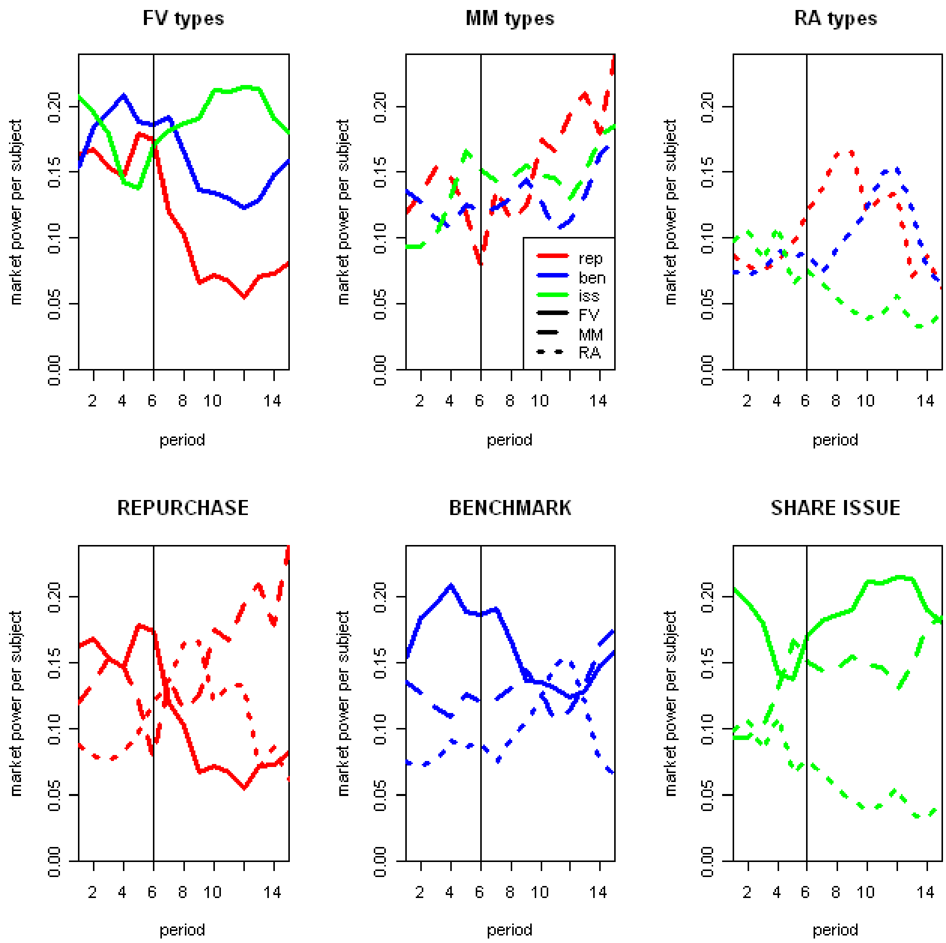
port for Hypothesis 7.

4.4.2 Market Power

Now consider how the interventions affect the market power that each type holds. In order to classify subjects, subjects are first assigned a period score that measures how well a subject's behavior in each period coincides with how each of the three theoretical trader types would have behaved (see Table 4.4 below). Then period scores are summed to get an aggregate measure of how well a subject's behavior coincides with each of the three types over the span of the entire market. He is then classified as belonging to the type for which he has the highest score, provided that he satisfies the condition corresponding to the type in at least 50% of all periods in the session. Those individuals not fitting any of the three types are classified as "other".

The first row of Figure 4.4 presents the average market power over time of an individual of each of the three different trader types, while the second shows market power for an individual of each trader type averaged over all sessions of a treatment. Turning first to the effect of an intervention in period 6, we find that the average FV type has more market power after a share issue than after a repurchase, and vice-versa for RA types. MMs also acquire considerably more market power in the latter periods of the Repurchase sessions. Thus it appears that the interventions have the effect of transferring market power to or away from FV types.

Figure 4.4: Market Power per Subject



Notes: Vertical bars indicate beginning of interventions.

Table 4.5 shows the average number of individuals in a market that are classified as belonging to each of the three types, by treatment. It shows that in the Repurchase treatment, more individuals are MM traders than in the other treatments. On the other hand, there are fewer FV traders in the Repurchase than in the other treatments. There are also more individuals classified as FV traders in the Share Issue than in the other treatments. Thus Hypothesis 8 receives strong support. More individuals act as FV traders in Share Issue than in Benchmark, and fewer act as FV traders in Repurchase than in benchmark. Furthermore, as shown in Table 4.3, the average FV trader has significantly more market power in the Share Issue than in the Repurchase treatment.

Table 4.5: Number of Traders by Type

Type	Repurchase	Benchmark	Share Issue
Rational	2.28	1.94	2.03
Momentum	3.86	2.94	2.53
Fundamental	2.53	3.28	4.11

Notes: Number of traders of each type, averaged over all sessions of a treatment.

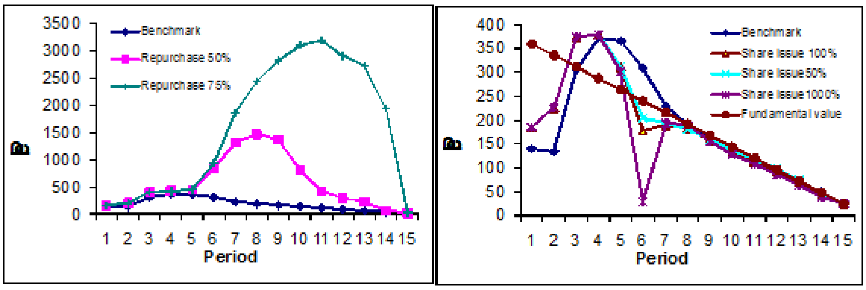
4.4.3 Interventions of Different Sizes

Now consider the potential effect of interventions of different sizes, with a focus on how robust the downward resistance of prices at fundamentals is to larger share issues. The results of simulations of several scenarios are given in Figure 4.5. In addition to simulations of the interventions conducted in the experiment, the figure contains average price paths resulting from buybacks of 75% of the total stock of units, as well as from share issues of 100% and 1000% of the initial stock of units[14].

The figure shows that a larger buyback creates a larger bubble, both in magnitude and duration. Comparison of the 75% and the 50% repurchases reveal a similar pattern in period 6 but higher prices thereafter under a larger repurchase. The larger share issues flood the market in periods 6, but the market tracks fundamental value closely afterward. Both cause the price to decrease in period 6, rebound in period 7, and then track fundamentals closely from period 8 onward. This indicates that the downward resistance of prices at fundamental values following a share issue is strong, even in the face of very large issues.

[14]In the simulations of share issues the entire supply of units can be and is sold in period 6, because there is a sufficient amount of disposable cash held by agents to purchase many units at very low prices. In the simulations of repurchases, it may take multiple periods for the intervention to be completed. A cash constraint for the repurchasing firm at 10,000 currency units per period is imposed in the simulations and the constraint is typically binding in periods 6 and 7. In the experiment, because of the 5-second interval between the submission of one of the firm's bids and the next, a constraint limiting the speed of completion of the intervention exists. The time available in period 6 sometimes expires before the experimenter has completed his intervention.

Figure 4.5: Simulated prices for additional interventions



Notes: Repurchases are for 50% and 75%, and share issues for 50%, 100% and 1000%, of the shares outstanding at the beginning of period 6.

4.5 Conclusion

In these experimental markets, repurchases and share issues are observed to have an impact on price levels, quite apart from any informational content they may provide to the market. The price effects of the interventions are found to be largely explained by a model of traders who follow particular momentum, rational, and fundamental trading strategies. The experimental results support the predictions from a simulation model that repurchases tend to remove power from traders who use fundamental values as a limit price, whereas share issues tend to concentrate power in the hands of fundamental value traders. This reallocation of weight to fundamental value traders that accompanies a share issue appears to move market prices closer to fundamentals. Further simulation results show a strong asymmetry between the two types of interventions.

Such findings are consistent with the evidence from empirical finance that asset demand is downward-sloping. During the dot com bubble of the late 1990s, there were stocks trading at what appeared to be extreme price-to-earnings multiples and investors lamented their inability to capitalize on these sure opportunities due to the constraints inherent in short selling (Ofek and Richardson (2003)). Furthermore, the effects of demand and supply of assets are apparent in other asset classes, including real estate (Lin and Yung (2006)), junk bonds (Kaplan and Stein (1993)), and emerging economies' debt (Krugman (1995)). It is clear how such markets might form bubbles as a result of demand-and-supply imbalances. It should thus not be surprising then that these factors play a role in stocks as well.

Of course, experiments do not contain many important features of stock markets, and the generality of the results hinges on how generic our environment is. As other work in the literature points out, the consequences on the firm's debt-equity balance, information signals, and tax positions of shareholders, are non-negligible. For example, knowing that issuing new shares lowers prices of all shares, firms would not pursue such a strategy unless they needed a new cash infusion to pursue a promising new investment or pay off debt that the company deems too expensive. This insight would in turn make new share issues non-neutral with respect to investor expectations of future payoff streams. A similar argument could be made regarding share repurchases. The research presented here clarifies the understanding of interventions by showing that they can still have a profound effect on relative demand and supply in the market, even controlling for the other consequences they might have on intrinsic values or on the beliefs of traders.

Other evidence for downward-sloping demand has been offered by Haruvy and Noussair (2006) with regard to short selling. In that work, short selling constraints are shown to be an important factor in bubble magnitude (also see F. et al. (1993)). Introducing a sufficient number of additional shares to the market through looser short selling restrictions created pricing below fundamentals. The short sellers tended to be the momentum traders and the rational speculators. In contrast, the increase in shares implemented here through the share issues results in the allocation of those shares primarily to the fundamental value traders. This helps to reduce mispricing rather than to increase it, as in the case of short selling.

Because of the change in the allocation of shares among types resulting from the two types of intervention, it appears that a larger repurchase would serve to persistently increase prices even more than in this experiment. Demand from momentum traders and rational speculators would be further encouraged, even as fundamental value traders, who would wish to sell, would run out of their units more quickly. On the other hand, a larger issue would not lower prices beyond fundamentals, at least not for longer than a period or two. The units the experimenter sells would be purchased primarily by the passive traders. This means that at the time of the intervention, fundamental traders would have more cash to buy units and would do so. This means that fundamental value traders would have a greater percentage of the shares after the issue, encouraging prices to track fundamentals even more closely. This is because they would have a greater ability to exploit any deviations from fundamentals in a manner that would push prices back toward intrinsic values.

Thus, our model predicts an asymmetry in the sense that relative to benchmark levels, prices will be pushed up more by a large repurchase of shares than they will be pulled down by a share issue of equal magnitude.

4.A Appendix

Subject Instructions

Instructions for experiment

1. General Instructions

This is an experiment on decision making in a market. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money, which will be paid to you in cash at the end of the experiment. The experiment consists of a sequence of trading Periods in which you will have the opportunity to buy and sell in a market. The currency used in the market is francs. All trading will be done in terms of francs. The cash payment to you at the end of the experiment will be in euros. The conversion rate is: 170 francs to 1 euro.

2. How to use the computerized market

In the top right hand corner of the screen you see how much time is left in the current trading Period. The goods that can be bought and sold in the market are called Shares. In the center of your screen you see the number of Shares you currently have and the amount of Money (francs) you have available to buy Shares.

If you would like to offer to sell a share, use the text area entitled “Enter offer to sell” in the first column. In that text area you can enter the price at which you are offering to sell a share, and then select “Submit Offer To Sell”. Please do so now. Type a number in the appropriate space, and then click on the field labeled “Submit Offer To Sell”. You will notice that nine numbers, one submitted by each participant, now appear in the second column from the left, entitled “Offers To Sell”. Your offer is listed in blue. Submitting a second offer will replace your previous offer.

The lowest offer-to-sell price will always be on the bottom of that list. You can select an offer by clicking on it. It will then be highlighted. If you select “Buy”, the button at the bottom of this column, you will buy one share for the currently selected sell price. Please purchase a share now by selecting an offer and clicking the “Buy” button. Since each of you had offered to sell a share and attempted to buy a share, if all were successful, you all have the same number of shares you started out with. This is because you bought one share and sold one share. Please note that if you have an offer selected and the offer gets changed, it will become deselected if the offer became worse for you. If the offer gets better, it will remain selected.

When you buy a share, your Money decreases by the price of the purchase. When you sell a share your Money increases by the price of the sale. You may make an offer to buy a unit by selecting “Submit Offer To Buy.” Please do so now. Type a number in the text area “Enter offer to buy”, then press the red button labeled “Submit Offer To Buy”. You can replace your offer-to-buy by submitting a new offer. You can accept any of the offers-to-buy by selecting the offer and then clicking on the “Sell” button. Please do so now.

In the middle column, labeled “Transaction Prices”, you can see the prices at which Shares have been bought and sold in this period. You will now have about 10 minutes to buy and sell shares. This is a practice period. Your actions in the practice period do not count toward your earnings and do not influence your position later in the experiment. The only goal of the practice period is to master the use of the interface. Please be sure that you have successfully submitted offers to buy and offers to sell. Also be sure that you have accepted buy and sell offers. If you have any questions, please raise your hand and the experimenter will come by and assist you.

3. Specific Instructions for this experiment

The experiment will consist of 15 trading periods. In each period, there will be a market open for 4 minutes, in which you may buy and sell shares. Shares are assets with a life of 15 periods, and your inventory of shares carries over from one trading period to the next. You may receive dividends for each share in your inventory at the end of each of the 15 trading periods.

At the end of each trading period, including period 15, the computer will randomly determine the dividend value for all shares in that period. Each period, each share you hold at the end of the period:

earns you a dividend of 0 francs with probability 1/4
earns you a dividend of 8 francs with probability 1/4
earns you a dividend of 28 francs with probability 1/4
earns you a dividend of 60 francs with probability 1/4

Each of the four dividend values is equally likely, thus the average dividend in each period is 24. Dividends are added to your cash balance automatically.

After the dividend is paid at the end of period 15, there will be no further earnings possible from shares.

——————— Insert only for Repurchase Treatment ————————————

4. Share Buyback

Over the course of the 15 periods, the computer will buy back half of the shares from the market. It will do so by submitting offers to buy shares. These offers will look and work exactly the same as offers created by other subjects. They will be listed under the "Offers to Buy" column and they can be accepted by using the "Sell" button. Once the computer has purchased back half of the shares, it will no longer participate in the market.

———————Insert only for Share issue Treatment ————————————

4. Share Sale

Over the course of the 15 periods, the computer will sell a number of shares on the market. The number of shares will equal half of the existing shares in the market. It will do so by submitting offers to sell shares. These offers will look and work exactly the same as offers created by other subjects. They will be listed under the "Offers to Sell" column and they can be accepted by using the "Buy" button. Once the computer has sold all of its shares, it will no longer participate in the market.

——————— End of Insert ————————————————————————

5. Average Holding Value Table

You can use your AVERAGE HOLDING VALUE TABLE to help you make decisions. There are 5 columns in the table. The first column, labeled Ending Period, indicates the last trading period of the experiment. The second column, labeled Current Period, indicates the period during which the average holding value is being calculated. The third column gives the number of holding periods from the period in the second column until the end of the experiment. The fourth column, labeled Average Dividend per Period, gives the average amount that the dividend will be in each period for each unit held in your inventory. The fifth column, labeled Average Holding Value Per Unit of Inventory, gives the average value for each unit held in your inventory from now until the end of the experiment. That is, for each share you hold for the

Table 4.6: Average Holding Value

Current Period (1)	Number of Remaining Dividends (2)	Average Dividend (3)	Average Remaining Dividends (4)
1	15	24	360
2	14	24	336
3	13	24	312
4	12	24	288
5	11	24	264
6	10	24	240
7	9	24	216
8	8	24	192
9	7	24	168
10	6	24	144
11	5	24	120
12	4	24	96
13	3	24	72
14	2	24	48
15	1	24	24

remainder of the experiment, you will earn on average the amount listed in column 5.

Suppose for example that there are 7 periods remaining. Since the dividend on a Share has a 25% chance of being 0, a 25% chance of being 8, a 25% chance of being 28 and a 25% chance of being 60 in any period, the dividend is on average 24 per period for each Share. If you hold a Share for the remaining 7 periods, the total dividend for the Share over the 7 periods is on average 7*24 = 168. Therefore, the total value of holding a Share over the 7 periods is on average 168.

6. Your Earnings

Your earnings for the entire experiment will equal the amount of cash that you have at the end of period 15, after the last dividend has been paid. The amount of cash you will have is equal to:

The cash (called “Money” on your screen) you have at the beginning of the experiment

+ dividends you receive

+ money received from sales of shares

- money spent on purchases of shares

The only limits are, as always, those of vision.

James Broughton

CHAPTER 5

INFORMATION AND SUBJECT FOCUS

This chapter examines subject focus in experimental asset markets using eye-tracking machines. First, changes in market performance (prices, trade volume) are related to subject focus, providing exploratory insights into how the processing of information precipitates market changes. Second, models of asset market behavior describe and predict the interaction of different types of traders in a market (De Long et al. (1990); Easley and O'Hara (1992)). This study is the first to examine how the visual attention of subjects in an asset market corresponds with the behavioral assumptions underlying the models. Finally, the study allows for the identification of how attention correlates with earnings, gender, and other subject characteristics.

5.1 Introduction

Of the five senses, vision may be the most important for modern humans. For example, the information contained here is most likely to be seen, and not heard, touched, smelled, or tasted. This is supported by the large fraction of brain resources devoted to processing visual information (Carlson et al. (2003)), and the extensive literature on how that part of the brain (the visual cortex) functions (see, for example, Bullier (2001) and Muggleton et al. (2003). This suggests that when it comes to absorbing information about an environment, vision plays a crucial role for humans and how they interact with their world. Economics, as a social science, aims to provide simplified models about how this interaction takes place. Often these models contain conjectures about how agents take decisions given the information they have acquired from their environment. Economic analysis has tended to focus more on the decisions themselves and less on the information acquisition process, at least in part because studying information acquisition has been relatively difficult to do. However, recent developments of unobtrusive eye-tracking equipment mean that this is no longer the case.

Information absorption, in other words what subjects observe in their environment, is important because it gives additional insights into how subjects make their decisions. In particular, it has the potential to help distinguish between multiple theories that might predict similar behavior in a given environment. The immediate task for many studies is to predict and explain behavior in a given research domain, in which case distinguishing between competing theories that provide similar predictions is of minor importance. However, once the broader task of predicting behavior outside of the immediate experimental setting is considered, it becomes necessary to filter out the good theories from the bad. It is in the support of this endeavor that eye-tracking in particular, and neuroeconomics in general, play a role (Camerer et al. (2005)).

The topic of information absorption has received an increasing amount of attention in economics. Two popular methods for tracking information acquisition are the use of mouse-tracking and eye-tracking systems. Mouse-tracking has been used rather extensively in many applications (see Payne et al. (1993) for a review). Recent examples in economics include applications to backward and forward induction (Johnson et al. (2002)), decision rules in normal-form games (Costa-Gomes et al. (2001)) and beauty contest games (Costa-Gomes and Crawford (2006)). The advantage of mouse-tracking is that it is easy to implement (free code that can be added to any web page), while the disadvantage is that cursor movement may only be roughly correlated with what subjects are focusing their attention on.

The recent advent of affordable eye-tracking machines means that tracking eye movements directly has become a possibility for many researchers. Eye-tracking uses systems of cameras, typically mounted on the computer screen, to monitor the size and gaze of subjects pupils. This allows for a much finer examination of subject attention than the mouse-tracking system. A recent example (Wang et al. (2009)) studies subject focus and pupil dilation in sender-receiver games.

So how can information acquisition, and eye-tracking in particular, help with the understanding of asset markets? The answer, described more fully in the sections that follow, is that it shows 1) how socio-demographic characteristics influence information acquisition in a financial task, 2) how asset market outcomes can be related back to the information that subjects actively monitor from their environment, and 3) whether or not particular trading strategies are based on accurate theoretical motivations. Additionally, models of asset market behavior describe and predict the interaction of different types of traders in a market (Back and Baruch (2007), De Long et al. (1990), Easley and O'Hara (1992)). This study also examines the consistency between the information absorption and trading activities of subjects classified according to these models.

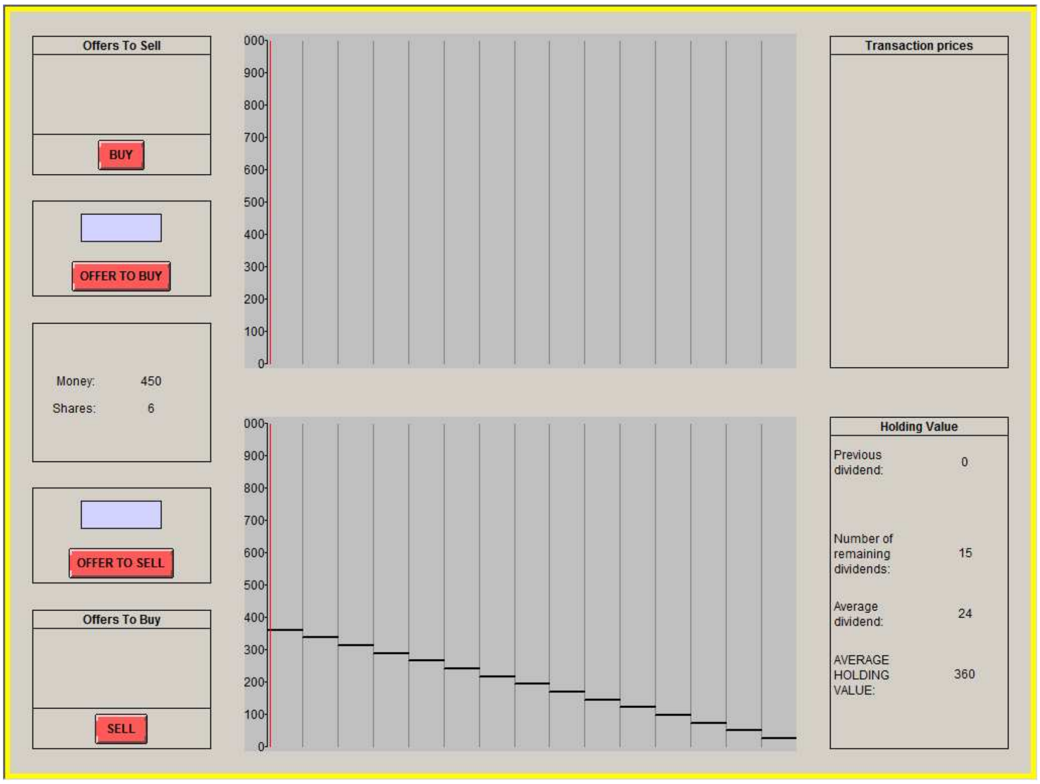
This study is then a first attempt to shed light on the information acquisition process in the context of experimental bubble markets. The design involves remotely monitoring the focus of subjects while they participate in a well-studied asset market setting. The bubble market setting is used because there exists a large literature of studies that use a similar framework, thus making the results of this study easier to relate to existing findings on asset market behavior. This allows for novel insights and suggestions as to how market and subject behavior is related to the information that subjects absorb from a bubble environment.

The results suggest that the addition of graphical elements to the interface, including a significant portion of the screen dedicated to explaining expected dividends, had little impact on performance. In combination with data on earnings, this means it is not possible to refute the idea that uncertainty about fundamentals drives the bubble creation process. Analysis of the eye-tracking data shows that personal characteristics do not predict differences in information absorption very well. Attention to dividends, independent of the level of dividends, also appears to play a role in predicting future price changes. Finally, the data show that there is some support for the 3-type model of De Long et al. (1990).

Due to the exploratory nature of this study, the hypotheses are incorporated directly into the discussion of the chapter, and not seperately as in the other study chapters.

5.2 Experimental Design

Figure 5.1: Trading Interface



The trading screen, shown in Figure 5.1, is divided into seven areas of interest that are labelled in Table 5.1. On the left is the trading area, which includes areas for 1) buying shares (top), 2) selling shares (bottom) and 3) inventory information (middle). The area associated with transactions is the upper-right area of the screen that shows the history of transactions, both as 4) a graph and 5) a list. The final area to the bottom-right of the screen presents information about dividends. It includes 6) a graph of the average expected returns over the course of the market, as well as 7) specific textual information regarding dividends, including information about the most recently received dividend.

The layout of the trading screen may potentially induce bias in subject behavior. If, for example, subjects are pre-disposed to focusing on elements in the top-left of the screen, this may induce purchasing bias in the markets (since the buying area is in the top left of the trading interface). Such a top-left bias has been documented for web-page usage (see, for example, Rodden et al.

Table 5.1: Screen Areas

Label	Description
buy	Purchasing.
sell	Selling.
inv	Inventory of cash and shares.
pgr	Graph of previous transaction prices for the entire market.
plis	List of previous tranaction prices in the current period only.
dexp	Graph of expected dividends for all periods.
dact	Actual value of the most recent dividend.

(2008)). However, there does not appear to be a persistent top-left bias for all visual tasks (see, for example, Tseng et al. (2009) for evidence of center bias, and Hagenbeek and Van Strien (2002), for bottom-left/top-right biases). But most importantly, all of the analysis done here deals with relative attention to different screen elements, so that the base level of attention is not important. For this reason the interface was simply designed to be as similar as possible to those used in similar studies (e.g. Haruvy et al. (2010)), while still making room for the visual elements.

The eye-tracking machines were calibrated during the middle of the training market. This was done to allow subjects to assume a natural posture in front of the computer, while not directly interrupting any market activity that would affect their final earnings. Only the market that determined earnings was recorded. See Appendix A for more details on the calibration of the eye-tracking machines.

5.3 Results

The dataset for this study consists of nine sessions of the market environment (described in Section 2.4). In each session, four subjects had their actions recorded by eye-tracking devices[1]. In order to facilitate comparison, parameter choices, shown in Table 5.2, were the same as those used in Chapter 4.

The analysis is divided into four parts. The first part shows that eye-tracking does not change behavior. The second part discusses some of the broad patterns in the data. The third part attempts to explain information absorption

[1]The lab has four eye-tracking machines. A few sessions had fewer than nine subjects. See Appendix 4.A for details.

Table 5.2: Design Parameters

Parameter	Value
Period length	120 seconds
Exchange rate	170 francs = 1 Euro.
Initial portfolios	(shares, cash) (6, 450); (4, 1170); (2, 1890)

patterns, while the section concludes by looking at how subsequent behavior is determined by previous information absorption.

5.3.1 Design Effects

This study differs from the design of Haruvy et al. (2010) in two major ways. First, some subjects had their screen focus recorded. Secondly, graphical elements were added to the interface. The effect of these design differences is given below.

The first concern is whether subjects sitting at eye-tracking machines behaved differently than subjects sitting at normal trading terminals. The conclusive answer, stated below, is that there does not appear to be any difference between the two types of subjects.

Result 5.1 *Eye-tracking has no effect on subject behavior at the level of the individual.*

Support for Result 5.1 : Consider the following regression:

$$y_i = \alpha + \sum_k \beta_k \cdot X_{i,k} + \gamma \cdot D_i + \epsilon_i,$$

where y_i, a given measure of the behavior of subject i, is modeled as a function of a set of controls $X_{i,k}$ and a dummy variable D_i that takes a value of unity if a subject had their vision tracked. The session subscripts are suppressed for clarity. The γ coefficient captures the effect that eye-tracking has on subject behavior.

Table 5.3 presents estimates of γ for various measures of subject behavior. In all cases, eye-tracking has a negligible effect on subject performance. This finding is particularly strong since the parametric structure of the regression

Table 5.3: Estimates of γ, the effect of eye-tracking on subject behavior

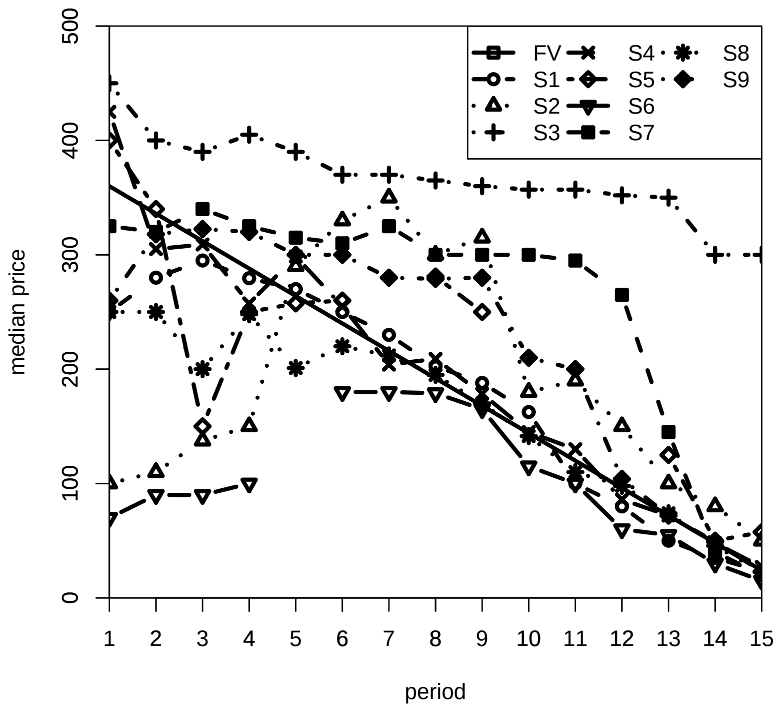
	Earnings	Trades	Offers	Share Holdings	Money Holdings
Estimate	-114.8	-6.2	-8.4	0.1	-70.7
Std. Dev.	(342.0)	(12.6)	(16.2)	(0.9)	(223.8)

Notes: Estimates from fixed-effects regressions, including controls for subject characteristics. Significance codes: 0 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1 . Standard errors in parentheses under coefficient estimates. Significance tests are relative to 0, $N = 77$. See Appendix for complete results.

model favors the finding of statistical significance relative to more conservative non-parametric tests. Therefore from the point of view of individual subject behavior, it does not appear that the changes to the experimental design had an effect on market outcomes.

The next point of interest is whether the interface changes, viewed by all participants, had an aggregate effect on the markets. In order to precisely quantify the effect of the interface, a comparison is made between these markets and similar markets from a closely related study (specifically, the markets from the *Benchmark* treatment in Haruvy et al. (2010)). The differences between the two sets of markets is that the markets in this study: 1) contained graphical information, and 2) ran continuously without pauses between periods, and 3) presented on-screen information relating to the fundamental value continuously throughout the experiment. The expected effect of the first two changes is unclear, however one might expect that the last change, making the information related to the fundamental value more prominent throughout the experiment, could increase the price discovery of the market, as was found in Lei and Vesely (2009).

Figure 5.2: Period Prices Relative to Fundamentals



Result 5.2 *The new interface, which includes extra salient information regarding dividends, does not have an overall effect on the level of price discovery.*

Support for Result 5.2 The median transaction price in each period of the sessions is presented in Figure 5.2[2]. A typical pattern of mispricing is observed in these markets. During the first few periods, prices tend to be consistently lower than fundamentals. As the market progresses, prices tend to creep upwards while at the same time fundamentals decrease. Around period 5 or 6, prices overshoot fundamentals, and a span of persistent over-pricing continues until period 12 or 13, at which point the bubble bursts and prices crash back towards fundamentals. At a glance, these markets appear to not differ substantially in their performance from previous work.

Levels of mispricing in these markets, as measured by bias, do not differ significantly from comparable markets reported in Haruvy et al. (2010) ($p > 0.3$, Wilcoxon ranksum test). In addition, the typical price patterns are not

[2]Periods in which there were no transactions were not included in the analysis.

Table 5.4: Screen focus and session outcomes, means and correlations

Variable	Session Mean	Earnings Corr.	Bias Corr.
Trade volume	102	-0.41	-0.01
Earnings	2555	1.00	-0.36
buy	39%	-0.60	0.53
sell	10%	0.07	0.12
inv	29%	0.17	-0.26
pgr	7%	0.41	-0.65
plis	3%	0.09	-0.11
dexp	5%	-0.29	0.15
dact	6%	0.68	-0.16

Notes: Focus variables are averaged over all periods of a subject, and then averaged over all subjects of a session. Other session values are computed as averages of subject values for that session. Correlations are between session-level values.

affected - prices tend to display under-pricing at the beginning of the market, followed by significant over-pricing for a period of time in the middle of the market, finally culminating in a crash to fundamentals near the end of the market.

5.3.2 Descriptive Statistics

The previous finding appears to be at odds with recent work by Lei and Vesely (2009). The aforementioned authors find that market efficiency is significantly increased when the fundamental value is made more salient to subjects, whereas here it appears to have no effect. Why does the additional information in this study, provided in a seemingly poignant visual manner, not appear to affect behavior, when it has such a strong effect in other work?

One possibility is that little attention was paid to the dividend sections of the screen. Perhaps subjects are so intensely focused on immediate trading possibilities that they have no time to look at information contained outside of the immediate order book. The eye-tracking data, summarized in Table 5.4, shows that this was not the case.

Subjects spent a little less than half of their time (column 1) looking at the purchasing and selling controls of the display (39% and 10%, respectively). A substantial amount of time was also devoted to looking at inventory (29%), but the remaining screen focus was devoted to price and dividend information. In particular, the areas of the screen devoted to dividends received a substantial amount of attention (11%) from subjects. Therefore it appears that lack of attention cannot explain the discrepancy.

A second possibility is that it is the nature of the dividend information that matters for price formation. It may be that the visual information presented in the display here differs from the type of information that is gained by receiving dividends (as in Lei and Vesely). The correlation between average subject earnings (determined exogenously by the dividend draws) and various session measures are shown in column 2. The negative value shows that higher dividends cause lower bias in these sessions. In the sense that higher dividends are also more dividends, this finding is consistent with Lei and Vesely who find that extra experience with dividends reduces market mispricing. This is summarized in the following observation.

Observation 1 *The ability of dividend information to mitigate price bubbles depends on the type of experience subjects receive with dividends.*

The last column of Table 5.4 shows that subjects pay less attention to the trading controls when earnings are higher. Instead, subjects tend to focus on historical prices and information about fundamentals. In other words, subjects like to sit back and count their money when times are good. Such a story is supported by the fact that earnings and trade volume are strongly negatively correlated. This effect of earnings on subject focus and market prices leads to the following observation:

Observation 2 *High prices are associated with less attention to previous trade information.*

The correlation between average bias in a session and the percentage of time subjects spent looking at various screen elements (given in column 3) shows that subjects tend to focus their attention, unsurprisingly, on the buying section of the screen during sessions with high prices.

What is surprising, however, is that this increased attention on the buying controls does not come at the expense of the selling controls (which actually receive slightly more attention as well), nor at the equal expense of all other screen elements. Instead, it comes almost entirely at the expense of the historical information on prices. Since historical price information is necessary when following a momentum trading strategy, this suggests that it is even less likely for subjects to be following a momentum trading during periods of over-pricing. In other words, bubbles may be more than simply the products of speculators following momentum trading strategies in the market.

This stands in stark contrast to studies such as Caginalp et al. (2000) that have found that momentum trading does a good job of explaining bubbles. Perhaps substantial opportunity still exists for improving the understanding of how bubbles work. For now, this is simply summarized in Observation 3:

Observation 3 *Bubbles are not correlated with the aquisition of information associated with a momentum trading strategy.*

5.3.3 Explaining subject focus

Having established that behavior in these markets is representative of behavior in other experimental work and highlighted some of the key features of the data, the analysis now turns to explaining subject focus in these markets. Self-reported answers to the subject survey are used to predict vision patterns.

There is some evidence that personal characteristics, for example gender (Charness and Gneezy (2007)) and ethnicity (Brown (2007)), have an effect on financial investment decisions. In contrast, the analysis that follows shows that very little of the differences in eye-tracking data is explained by differences in subject characteristics. This is summarized in Result 5.3:

Result 5.3 *Subject characteristics are not important determinants of screen focus.*

Support for Result 5.3 : In order to estimate the effect of subject characteristics on screen focus, consider regressions of the form:

$$aoi_i = \alpha_i + X_i\beta + \epsilon_i,$$

where aoi_i is the *absolute* time that subject i spent looking at an area of interest over the entire market, and X_i are the personal characteristics of the subject. The β elements measure the effect of various subject characteristics on screen focus.

Subject behavior, in terms of focus on screen elements, is remarkably stable over various types of characteristics (see Table 5.5 for estimates, Appendix 5.A for questionnaire details). Considering gender, the only statistically significant differences are that males spend less time looking at textual information regarding fundamentals, instead focusing more time on textual information regarding prices. Large differences do not appear to be driven by ethnicity, years of education, or experience with experiments or trading environments. The only other strong effect appears to be the choice of major. Overall, business students spent more time looking at screen elements. The most striking difference appears to be related to dividends - business students spend significantly more time looking at actual dividends, whereas students from economics and other majors tend to focus more on expected dividends.

The previous analysis investigated whether average subject vision patterns over an entire market could be explained by subject characteristics. The following explores whether such a relationship exists between *period to period* variables.

Throughout the lifetime of the market, the value of subjects' portfolios fluctuates, both because of changes in the market price of shares and the size of received dividends. A natural hypothesis in this setting is that the rate of strategy search depends on previous subject performance. Particularly, subjects who feel that their trading strategy has been more successful (due to a recent increase in portfolio value) will be less likely to search for new information, whereas those with poor performance will be more likely to increase their examination of different screen elements in the hopes of improving their trading strategy.

This hypothesis is tested by estimating the parameters of:

$$\Delta y_{i,t} = \alpha_i + X_{i,t}\beta + \gamma \Delta pv_{i,t-1} + \epsilon_i,$$

where $y_{i,t}$ is search activity of subject i in period t, $pv_{i,t}$ is the market value of subject i's portfolio at the end of period t, and $\Delta x_t = x_t - x_{t-1}$. $X_{i,t}$ is a set of control variables that include a time trend and the personal characteristics of subject i. A time trend is included to allow for the fact that subjects may tend to naturally decrease their search activity over time, for example due to learning effects. Search activity is proxied by the total time spent looking at the screen.

Estimates (see appendix) of the parameters of this regression are suggestive. First, as expected, the coefficient on the time trend is negative and highly significant. This means that subjects do have a tendency to decrease their screen attention over time. Secondly, the coefficients on the subject characteristics are all insignificant, suggesting that patterns of changes are not related to socio-economic variables. Finally, the estimate of γ is positive, but insignificant ($p > 0.5$). Thus search activity is *not* related to recent changes in portfolio value, suggesting that subjects do not engage in more search after observing large swings in their portfolio value. This is summarized as Result 5.4.

Table 5.5: Screen focus and subject characteristics

Variable	Area of interest						
	buy	*sell*	*inv*	*plis*	*pgr*	*dact*	*dexp*
Gender (Female)							
Male	46.0	-71.3	5.7	13.5*	-16.5	-36.6**	1.7
	(64.0)	(56.1)	(15.3)	(7.2)	(25.1)	(14.4)	(14.9)
Ethnicity (North American)							
Dutch	101.7	41.9	-35.0	3.2	-9.8	24.9	13.4
	(98.9)	(86.8)	(23.7)	(11.1)	(38.8)	(22.2)	(23.0)
Other	-33.3	-78.5	0.4	1.1	39.3	20.0	-26.8
European	(92.4)	(81.1)	(22.1)	(10.3)	(36.3)	(20.8)	(21.5)
South	-201.5	-66.2	45.1	-18.5	-31.3	36.2	56.5
American	(168.0)	(147.5)	(40.2)	(18.8)	(66.0)	(37.8)	(39.1)
Other	121.9	208.8*	63.8*	-2.9	-43.9	-15.5	93.6***
	(130.9)	(114.9)	(31.3)	(14.6)	(51.4)	(29.4)	(30.5)
Major (Business)							
Economics	-92.1	-16.1	6.1	-2.2	-7.7	-41.9**	15.6
	(68.3)	(59.9)	(16.3)	(7.6)	(26.8)	(15.3)	(15.9)
Other	-27.9	2.2	27.3	-19.9	-39.3	-50.4	43.7
	(99.2)	(87.1)	(23.7)	(11.1)	(39.0)	(22.3)	(23.1)
Years of education (1)							
2	212.6**	63.1	39.4	17.0	37.0	23.2	27.3
	(100.6)	(88.3)	(24.1)	(11.3)	(39.5)	(22.6)	(23.4)
3	2.5	-21.5	2.3	18.4	21.5	17.2	-26.8
	(110.5)	(97.0)	(26.4)	(12.4)	(43.4)	(24.9)	(25.7)
4+	132.5	93.2	6.0	7.8	25.5	36.6*	10.0
	(94.1)	(82.6)	(22.5)	(10.5)	(37.0)	(21.2)	(21.9)
Experiment experience (No)							
Yes	-2.4	-119.6	-26.5	6.2	51.9	-66.1*	-16.0
	(142.7)	(125.3)	(34.1)	(16.0)	(56.0)	(32.1)	(33.2)
Trade experience (No)							
Yes	7.2	108.5	28.9	-2.7	-28.4	3.4	16.6
	(76.9)	(67.5)	(18.4)	(8.6)	(30.2)	(17.3)	(17.9)

Notes: Screen focus variables are the *absolute* length of time a subject spent looking at a screen area. Fixed-effects regressions. Significance codes: 0 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1. Standard errors in parentheses under coefficient estimates. Significance tests are relative to the reference levels given in parentheses following the variable names. N = 33.

Result 5.4 *Changes in search activity are not related to subject characteristics or changes in portfolio value.*

The investigation now turns away from explaining subject focus to considering its effect on market behavior.

5.3.4 Effects of subject focus

Consider how market performance in a particular period depends on previous subject focus. Specifically, consider how observables in period t of a session depend on average subject attention in period $t-1$ of the same session. The following result shows that short-term market behavior is strongly related to screen focus.

Result 5.5 *Attention to anything other than current dividends causes* Bias *to be relatively smaller in the future. More attention to current dividends causes larger subsequent price increases.*

Support for Result 5.5 Consider a regression of the form:

$$y_t = \alpha + \sum_i \beta_i \cdot aoi_{i,t-1} + \epsilon_t,$$

where y_t is a measure of interest in period t of a session, and $aoi_{i,t-1}$ is the percentage of time subjects spent looking at area of interest i in the period $t-1$. The β coefficients measure the effect of screen focus on the subsequent value of the measure y_t. Specifically, β_i measures how much larger the measure of interest would have been if subjects had on average spent 1% more of their time looking at focus area i. The session subscript has been omitted for reasons of clarity. The results are reported in Table 5.6.

The first column shows that focusing on anything other than actual dividends (the reference level for the regression) relatively decreases the size of future biases. Conversely, focusing on realized dividends increases future biases in prices. This suggests that a preoccupation with current dividends may spur the formation of bubbles. The results of a similar regression on the number of transactions in a period (column 3) are less statistically significant, however still support the pattern observed with respect to bias. High volume is most strongly preceded by attention to current dividends, suggesting that looking at current dividends may drive demand up, increasing both prices and the amount of trade in a period. Additionally, allowing for the size of previous

Table 5.6: Regressions of period focus on percentage change in bias and volume

Variable	$bias_t$		vol_t		$\%\Delta bias_{t+1}$		$\%\Delta vol_{t+1}$	
buy_{t-1}	15.4	-106.4	-7.8	-10.3	-45.7***	-35.8	-5.2	-6.8
	(213.9)	(280.8)	(14.9)	(19.1)	(16.0)	(20.5)	(3.7)	(5.3)
$sell_{t-1}$	38.9	-357.3	-8.7	-18.3	-35.0**	-28.4	-4.8	-7.2
	(214.4)	(277.4)	(15.0)	(18.8)	(16.0)	(20.4)	(3.8)	(5.2)
inv_{t-1}	42.1	-562.4	-34.1**	-63.4	-36.3*	-16.9	-10.4**	-16.5**
	(288.6)	(402.6)	(20.3)	(27.6)	(21.2)	(29.1)	(5.2)	(7.5)
$plis_{t-1}$	309.5	412.3	-3.0	-8.0	-43.6**	-20.1	-3.1	-6.1
	(288.4)	(386.0)	(20.3)	(26.7)	(21.4)	(27.9)	(5.1)	(7.2)
pgr_{t-1}	383.7	-72.8	8.6	-8.9	-31.9	-28.5	-1.0	-6.6
	(298.9)	(416.7)	(20.8)	(28.0)	(21.9)	(30.4)	(5.2)	(7.7)
$dexp_{t-1}$	347.3	833.7	-3.6	-2.8	-55.8	-48.4	-7.6	-16.5
	(475.2)	(694.8)	(33.8)	(48.3)	(34.5)	(49.1)	(8.4)	(12.9)
d_{t-1}		-0.3		0.02		-0.01		-0.0
		(0.3)		(0.02)		(0.02)		(0.0)
d_{t-2}		-7.4		-0.24		0.37		-0.0
		(9.4)		(0.61)		(0.67)		(0.2)
$d_{t-2}\times$		3.8		0.04		-0.24		-0.0
buy_{t-1}		(9.8)		(0.62)		(0.70)		(0.2)
$d_{t-2}\times$		12.5		0.32		-0.40		0.0
$sell_{t-1}$		(9.7)		(0.64)		(0.69)		(0.2)
$d_{t-2}\times$		23.8*		0.98		-0.64		-0.0
inv_{t-1}		(13.4)		(0.90)		(0.94)		(0.2)
$d_{t-2}\times$		-6.5		0.05		-0.61		0.1
$plis_{t-1}$		(13.0)		(0.88)		(0.93)		(0.2)
$d_{t-2}\times$		16.4		0.87		-0.36		0.2
pgr_{t-1}		(13.6)		(0.85)		(0.96)		(0.2)
$d_{t-2}\times$		-31.7		-0.91		-0.03		0.2
$dexp_{t-1}$		(25.5)		(1.73)		(1.82)		(0.5)
N	119	110	123	114	112	104	119	110

Notes: Fixed-effects regressions. Significance codes: 0 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1. Standard errors in parentheses under coefficient estimates. Significance tests are relative to the effect of $adiv_{t-1}$.

dividends (reported columns 2 and 4) does not change the main findings. Dividend size in the period preceding the recording of subject focus reduces the differential impact between looking at dividends and the rest of the screen, although this effect is quite mild.

A specific type of price change in bubble markets is the crash that occurs when the bubble implodes. The previous result suggests that these crashes are preceded by shifts in attention away from realized dividends to other parts of the screen. Analysis of the three sessions that experience large price crashes leads to the following observation:

Observation 4 *Crashes are immediately preceded by an absolute decline in attention to purchasing opportunities, while during the early stages of a crash attention immediately returns to the purchasing area at the expense of the selling area.*

The data underlying this observation are presented in Table 5.7. It shows for each of the sessions that experienced a large crash, the size of the subsequent crash (measured as the average percentage decrease in price per period remaining in the market), along with changes in the level (first rows) and proportion of attention (second rows) accorded to each area of the screen.

Consider, for example, Session 2 (column 2). Just before the crash (periods 6 & 7), subjects on average decreased the amount of attention they paid to the purchasing section of the screen by 7.4 seconds (or almost 5%). During the crash which began in period 8, subjects *increased* their attention to the purchasing area by 16 seconds (or about 8%) while decreasing their attention to the selling area by almost the same amount (10.6 seconds, or 7.4%). This pattern holds for all three crashes, thus it appears to be a general pattern that impending crashes are foreshadowed by a sharp drop in attention to the buying section of the screen, whereas once the crash has started attention shifts back to the purchasing area (mostly at the expense of the selling area).

This combination of findings is suggestive of how experience with dividends might play a role in determining bubble sizes. Specifically, subjects may simply be unfamiliar with dividends and thus extropolate higher earnings in the future from the dividends they currently receive. The graphical presentation of dividend information does not by itself help subjects establish accurate beliefs about expected dividends. This would explain why in settings where subjects have experience with receiving real dividends, bubbles tend to decrease in size (such as in Lei and Vesely (2009), where subjects have a special training phase for dividends, and such as in Noussair and Powell (2010), where subjects participate in repeated markets).

Table 5.7: Subject focus before and during crashes

Session	S2		S7		S9		Mean	
Size	10%		19%		11%		13%	
t	t^*-1	t^*	t^*-1	t^*	t^*-1	t^*	t^*-1	t^*
Δbuy_t	-7.4	16.08	-28.43	25.46	-14.98	12.71	-16.94	18.09
%	-0.05	0.08	-0.13	0.15	-0.03	0.01	-0.07	0.08
$\Delta sell_t$	11.03	-10.65	5.37	-13.16	34.73	-8.76	17.04	-10.85
%	0.08	-0.07	0.02	-0.02	0.15	-0.04	0.08	-0.04
Δinv_t	1.32	0.98	5.81	-1.24	-7.95	10.79	-0.27	3.51
%	0.01	0	0.03	0	-0.05	0.02	0	0.01
$\Delta plis_t$	-1.51	0.56	4.75	-4.6	1.44	1.89	1.56	-0.72
%	-0.04	-0.03	0.03	-0.05	-0.01	0.01	-0.01	-0.02
Δpgr_t	2.49	3.9	12	-14.05	-5.54	-7.61	2.98	-5.92
%	0.02	0.03	0.04	-0.05	-0.03	-0.03	0.01	-0.02
$\Delta dexp_t$	-5.38	-3.79	6.04	-11.21	-2.69	5.4	-0.68	-3.2
%	-0.01	0	0.02	-0.01	0	0	0	0
$\Delta dact_t$	-2.13	-2.75	-3.25	-5.5	-6	5.95	-3.8	-0.77
%	-0.01	-0.02	-0.01	-0.02	-0.03	0.01	-0.02	-0.01

Table 5.8: Effect of subject attention on change in share holdings relative to actual dividends

	Area of Interest					
	buy_{t-1}	$sell_{t-1}$	inv_{t-1}	$plis_{t-1}$	pgr_{t-1}	$dexp_{t-1}$
Estimate	-2.12***	-1.17*	-4.23***	-2.44**	-0.81	-4.03
	(0.55)	(0.66)	(1.57)	(1.18)	(1.11)	(4.09)

Notes: Fixed-effects regression. Dependant variable is Δs_t. Significance codes: 0 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1. Standard errors in parentheses under coefficient estimates. Significance tests are relative to estimate of $dact_{t-1}$. N = 72.

Having established that screen focus is an important predictor of certain market outcomes, this section considers whether screen focus can predict individual behavior as well. Here the analysis is restricted to the context of subject optimism. In particular, does subject focus predict whether or not a subject will accumulate shares in the near future?

Result 5.6 *Subject holdings increase most when subjects have been looking at received dividends. They decrease most following attention to inventory.*

Support for Result 5.6 Table 5.8 shows how changes in subject holdings, s_t, are related to how a subject divided up their attention in the previous period of the market. Subjects who spent more time looking at actual dividends (the reference level) were the most likely to increase their share holdings. On the other hand, it appears that share offloading was most likely to be preceded by subjects spending time looking at their inventory. Therefore it appears that changes in share holdings are most directly driven by concern for a subject's own earnings and inventory. They do not appear to be caused by a strategy that relies on predicting future price changes on the basis of the order book, which would have involved the buy or sell areas of interest, or previous trade prices, which would have used the pricing screen areas.

The previous findings suggest that subject behavior depends on which types of information subjects choose to absorb. One question that follows naturally from this is whether different subjects look at different information because they follow distinct trading strategies.

De Long et al. (1990) propose three types of traders populating a market: fundamentalists, momentum traders, and hyper-rational forecasters. The table below summarizes the information which each trader type uses when

Table 5.9: Signals for Trader Types

Type	Signal
Fundamentals traders, FV	$-bias_{t-1}$
Rational speculators, RA	$\Delta bias_{t+1}$
Momentum traders, MM	$\Delta bias_{t-1}$

Notes: The sign of the change in share holdings, Δs_t^i, is the same as the signal sign.

determining whether to increase or decrease their share holdings over time. This information is called the trader's *signal*, where positive signals mean the trader will increase their share holdings, and negative signals mean the trader will be a net seller of shares in the current period. All signals are defined in terms of the *period bias*.

Table 5.9 shows how each trader type behaves. Fundamental value traders (FV) increase their share holdings when shares are currently under-priced. Rational speculators (RA) correctly anticipate the next period's price movement and buy shares in the current period if shares will become more over-priced in the next period. Finally, momentum traders (MM) increase share holdings if bias has been increasing in the recent past. When the conditions for increasing share holdings are not met, share holdings are decreased (or held constant if a signal of zero is received).

Given these theoretical benchmarks, actual traders are classified according to the following rules, adapted from Haruvy et al. (2010) [3]. A score for each period is assigned to each trader based on how strongly their behavior coincides with how each theoretical trader type would have behaved in that period. Then the cumulative period scores are used to give a final measure of the extent to which a subject acted as each of the trader types.

The classification relies on the proportion of subject i's wealth that is held in stocks versus cash in period t, referred to as portfolio position, $pp_{i,t}$. Formally,

$$pp_{i,t} = s_{i,t}/s_{i,t}^{max},$$

where $s_{i,t}$ and $s_{i,t}^{max}$ are the actual and maximum share holdings of subject i at the end of period t (where the maximum share holdings are determined using

[3]This classification differs from the previous one in a few ways: first, period scores are weighted according to the magnitude with which a subject behaved like a trader type, and also according to the strength of the signal received; second, subjects are not uniquely classified as one type of trader or another; finally, signals depend on bias, and not solely price.

cash holdings $c_{i,t}$ and the median transaction price p_t, so that $s_{i,t}^{max} = s_{i,t} + c_{i,t}/p_t$). Taking into consideration that relative portfolio positions naturally tend to decrease as dividends are injected into the market, these positions are always considered relative to the average portfolio position of all subjects in the market.

For each period t, a trader is given a score for each type depending on the change in the subject's relative portfolio position between the beginning and end of the period, $\Delta_t pp = pp_t - pp_{t-1}$. This difference is used in conjunction with the force of the signals that each type of trader would have received in a period to calculate scores for each trader type in each period. Specifically,

$$score_t = \Delta_t pp/signal_t,$$

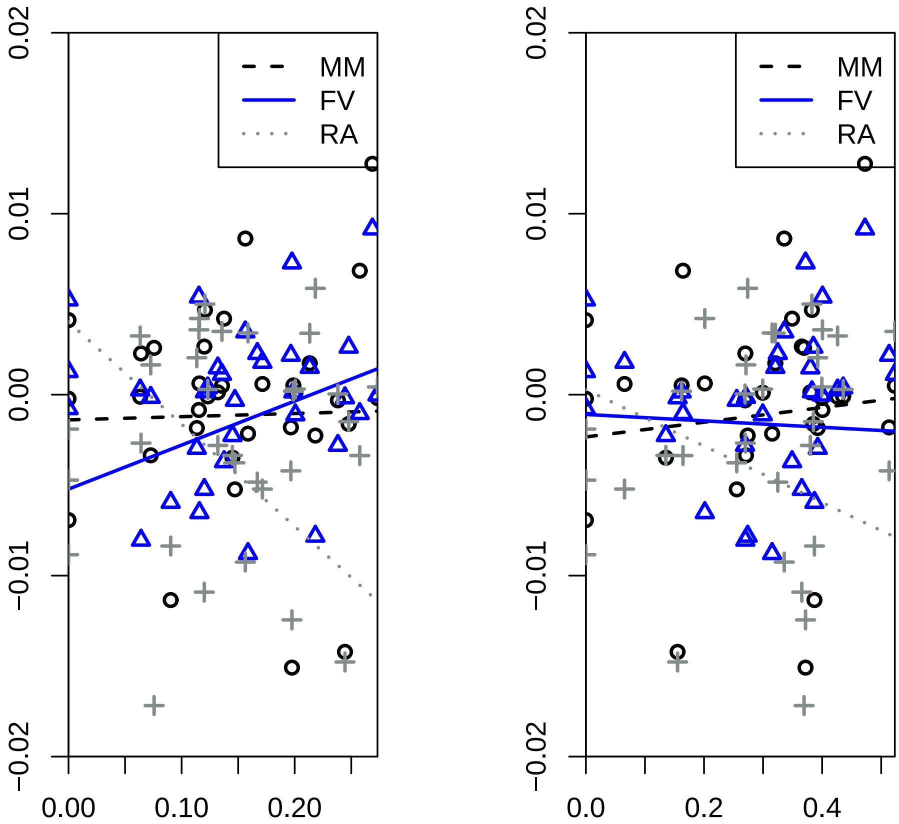
where $score_t$ is the subject's score for period t, $signal_t$ is the signal during that period (see Table 5.9).

Recall that different types of information are required to follow different types of trading strategies. In particular, fundamentalists require information about current prices and current fundamentals, whereas momentum traders look back in time to previous prices and previous fundamentals to make their portfolio decisions. This provides a clear hypothesis in terms of screen focus: the more strongly a subject follows one of the three trading strategies, the more time they should spend looking at the information that is relevant for that trading strategy.

In terms of the specific interface used in this experiment, this means that momentum traders, who are the only ones who trade on the basis of historical information, should spend the most time looking at the price graph and the graph of fundamentals, since these are the only sources of historical information regarding previous periods. Similarly, fundamental traders, who trade only on the basis of current price and fundamentals information, should be most likely to focus their attention on current transaction prices, given in the price list, and current fundamentals, given most explicitly in the area concerning actual dividends. Thus the theory clearly predicts different focal areas of interest for these two different types of traders.

The relationship between how strongly subjects followed each trading strategy and the relative amount of attention paid to each types focal point of interest is given in Figure 5.3. The panels present relative attention to the focal area on the horizontal axis and classification scores on the vertical axis. To the extent that the description above is true, the more highly a trader is scored as a particular type, the more time they should have spent looking at the focal area for their type. This turns out to be the case for Momentum types (first panel). As a subject pays higher levels of attention to the information that momentum traders are associated with, a subject is more and more likely to be classified as a momentum type than a fundamentalist. For attention to fundamentalist information, this is also the case. The more attention is paid to current period information that fundamentalists are assocated with, the more likely a subject is to be classified as a fundamentalist.

Figure 5.3: Type scores and areas of interest



Given the relatively small number of observations, it is not surprising that these findings are not statistically significant. However it does appear that there is at least some support for the 3-trader classification scheme. On the basis of this study, it appears that given the information that subjects have chosen to seek out from the trading screen, they subsequently behave in the ways predicted by the model. This provides another piece of evidence suggesting that the trading models may provide fruitful insights in future research.

5.4 Conclusion

This study explores how outcomes in laboratory asset markets are related to the information that subjects visually collect from their environment. Several different aspects of the setting are examined, in the hopes of providing initial observations that may provide useful for future research undertakings.

In the context of experimental design, the addition of graphical elements is found to not have a strong effect on outcomes. While a significant amount of attention is paid to the graphical sections of the display containing dividend information, this information is found to not have a profound effect on price efficiency. This suggests that the sensitivity of bubble formation to dividends may not be because subjects find the raw information about dividends difficult to digest. It could simply be that initially subjects do not fully understand the content of dividend information and how it affects their earnings. This would explain why bubbles are not eliminated in the setting studied here, but can be eliminated when subjects receive real dividends, as they do when market settings are repeated, or in training phases such as that of Lei and Vesely (2009).

The results from the market analysis also support such an interpretation. Price increases tend to be preceded by extra attention being paid to the section of the screen where the most recently received dividends are displayed. This suggests, although does not prove, that bubbles may be instigated by increases in individual expectations regarding future dividends, and not on the basis of gains expected from buying low and selling in the future at a high price. This stands in contrast to the description of a bubble put forward by Kindleberger and Aliber (2005), who suggests that bubbles are driven by capital gains expectations. Additionally, crash episodes are found to be most prominently precipiated by shifts away from and back towards the purchasing area of the screen.

Individual subject behavior reveals several interesting patterns. First, information selection by subjects is not very sensitive to personal characteristics. Ethnicity, years of education, and experience in similar experimental settings to not have a strong effect on where subjects focus their attention. The only mildly influential variables appear to be gender and choice of major, although neither is as strong as would be expected given findings in other financial settings. Secondly, large changes in share holdings appear to be preceded by extra attention to inventory and dividend areas of the screen, as opposed to areas of the screen containing transaction information. This also suggests that subjects trade without a motive to capitalize on price changes; instead they are focused on the direct accumulation of dividends. Finally, this study provides some support for a three-type classification of traders. Traders tend to behave in ways consistent with what the model predicts they would do, given their distribution of attention to the screen.

Perhaps most importantly, this work provides an example of how eye-tracking methods may be applied to asset market research. As the quote at the beginning of the paper makes clear, taking vision directly into account may allow for many types of analyses that have previously been hidden from the research agenda.

5.A Appendix

The TOBII EYE TRACKER IS eye-tracking machines were calibrated using the default settings recommended for a combination of images and text (see Table 5.10) for Clearview 2.7. The system records the duration, time-stamp and screen coordinates of subjects' screen fixations every 3 milliseconds. Pupil dilation data is also collected. More information is available from the Tobii website: www.tobii.com.

Table 5.11 contains a summary of the experimental data for all sessions of the study. This is followed by the subject instructions, the text of the questionnaire, and a listing of additional regression results.

Table 5.10: Eye-tracker settings

Setting	Value
Eye:	Normal
Fixation radius:	30
Min. duration	100
Screen resolution:	1024 x 768
Screen size:	19″

Table 5.11: Session Information

Session	1	2	3	4	5	6	7	8	9
# of subjects	9	9	8	9	9	7	9	9	8
Bias	-184.5	-47.5	2636.0	69.5	197.0	-1187.0	1045.0	-442.5	437.5
buy	0.29	0.34	0.48	0.46	0.38	0.39	0.47	0.41	0.35
sell	0.10	0.09	0.10	0.07	0.10	0.09	0.12	0.13	0.11
inv	0.40	0.36	0.25	0.34	0.25	0.24	0.19	0.29	0.34
pgr	0.08	0.08	0.05	0.04	0.08	0.13	0.07	0.06	0.07
plis	0.03	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.02
dexp	0.04	0.06	0.07	0.02	0.06	0.07	0.03	0.05	0.05
dact	0.07	0.05	0.03	0.04	0.11	0.07	0.09	0.03	0.07

Due to technical difficulties, two eye-tracking subjects were not recorded. Due to attendance problems, in two sessions only 8 subjects were used and in one session only 7 subjects were used.

Subject Instructions

1. General Instructions

This is an experiment on decision making in a market. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money which will be paid to you at the end of the experiment. The experiment consists of a sequence of trading Periods in which you will have the opportunity to buy and sell in a market. The goods that can be bought and sold in the market are called Shares. The currency used in the market is francs. The cash payment to you at the end of the experiment will be in euros. The conversion rate is: 400 francs to 1 euro.

The experiment is organized as follows. First, everyone reads these instructions and participates in a practice period. Following the practice period, more instructions will be given, and then the real market will begin. Your earnings only depend on your actions in the real market. It will be made very clear when the real market begins.

2. How to use the computerized market

Trading is conducted by making offers to buy and sell shares for francs. The screen is divided into 5 parts (see picture).

PART 1: INVENTORY The number of Shares and Money you currently have.

PART 2: BUYING Here you can "Offer to buy" a share, or "Buy" a share directly from someone who has offered to sell a share. When you buy a share, your Money decreases by the price of the purchase.

To make an offer to buy, enter the price at which you are offering to buy a share, and then click the "Offer to buy" button. Your offer will now appear under "Offers to Buy" in the bottom-left of the screen (part 3).

To buy a share directly, click on an offer from the "Offers to Sell" list, then press "Buy". You will then buy one share for the currently selected price.

PART 3: SELLING Here you can "Offer to sell" a share, or "Sell" a share directly to someone who has offered to buy a share. When you sell a share your Money increases by the price of the sale.

To make an offer to sell, enter the price at which you are offering to sell a share, and then click the "Offer to sell" button. Your offer will now appear under "Offers to Sell" in the top-left of the screen (part 2).

To sell a share directly, click on an offer from the "Offers to Buy" list, then press "Sell". You will then sell one share for the currently selected price.

Your offers are always listed in blue. Submitting a second offer will replace your previous offer. If you have an offer selected and the offer gets changed, it will become deselected if the offer became worse for you. If the offer gets better, it will remain selected. It is not possible to borrow money or shares.

PART 4: PRICES & TIME The prices at which Shares have been bought and sold in the market. Squares indicate trades. The moving red bar indicates the time left in the market.

PART 5: The bottom-right area of the screen will be explained later.

3. Practice Period

You will now have about 10 minutes to buy and sell shares in a practice period. Your actions in the practice period do not count toward your earnings and do not influence your position later in the experiment. The only goal of the practice period is to master the use of the interface. Please be sure that you have made offers to buy and offers to sell. Also be sure that you have accepted buy and sell offers.

If at any time you have any questions or concerns, the experimenter will come by and assist you.

4. Specific Instructions for this experiment

The experiment will consist of 15 trading periods, denoted by gray bars on the graphs. In each period, there will be a market open for 2 minutes in which you may buy and sell shares. Shares are assets with a life of 15 periods. Your inventory of shares and money carries over from one trading period to the next. You may receive dividends for each share in your inventory at the end of each of the 15 trading periods.

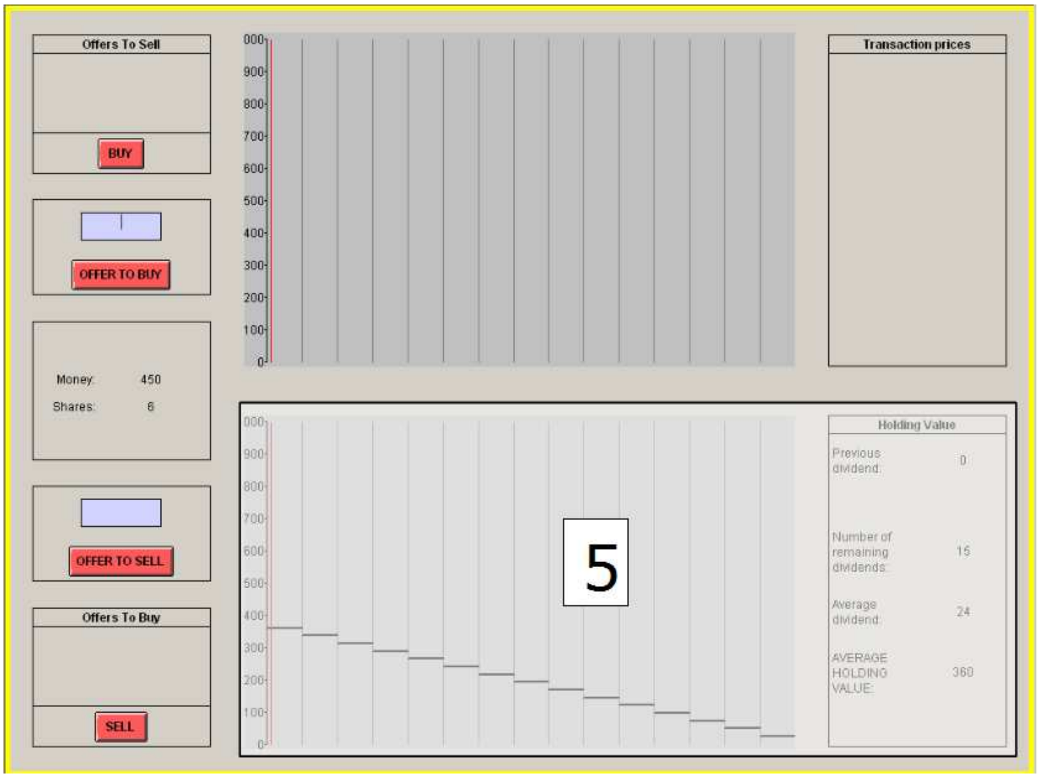
At the end of each trading period, including period 15, the computer will randomly determine the dividend value for all shares in that period. Each period, each share you hold at the end of the period:

earns you a dividend of 0 francs with probability 1/4
earns you a dividend of 8 francs with probability 1/4
earns you a dividend of 28 francs with probability 1/4

earns you a dividend of 60 francs with probability 1/4

Each of the four dividend values is equally likely, thus the average dividend in each period is 24. Dividends are added immediately to your cash balance when they are received. After the dividend is paid at the end of period 15, there will be no further earnings possible from shares.

PART 5: AVERAGE HOLDING VALUE



The last part of the screen indicates information related to dividends. There are 4 amounts listed. The first, "Previous dividend", is the amount of the last dividend, if any, you received on your shares. The next is the "Number of remaining dividends" for a share. The third amount is the "Average dividend" in each period, and is always 24 francs. The final value, the "AVERAGE HOLDING VALUE", is the average amount of dividends you will receive for holding a share in your inventory from the current period until the end of the experiment.

Suppose for example that it is Period 14. Then there are 2 trading periods remaining in the market, and also 2 dividends remaining on a share. Since the average dividend on a Share is 24, if you hold a Share for the remaining 2 periods, the total dividends for the Share over the 2 periods will on average be 2*24 = 48. Therefore, the average value of holding a Share over the 2 periods is 48 francs.

The graph shows the average holding value over all 15 periods.

5. Your Earnings

Your earnings for the entire experiment will equal the amount of cash that you have at the end of period 15, after the last dividend has been paid. The amount of cash you will have is equal to:

The cash (called "Money" on your screen) you have at the beginning of the experiment

+ dividends you receive

+ money received from sales of shares

- money spent on purchases of shares

Questionnaire

1. Gender:

[Male / Female]

2. Ethnicity you most associate with:

[Dutch / Other European / Asian / African / North American / South American / Other]

3. Area of study:

[Business / Economics / Other]

4. Years of university study:

[1 / 2 / 3 / 4+]

5. Have you previously participated in economics experiments?:

[Yes / No]

6. Have you previously participated in economics trading experiments?:

[Yes / No]

Additional Regression Results

This section includes results on aggregate subject behavior as a function of subject characteristics and whether or not they used an eye-tracking device.

```
> subjects$y = subjects$Earnings
Oneway (individual) effect Within Model

Call:
plm(formula = fm, data = curData, model = "within", index = c("Session",
    "Subject"))

Unbalanced Panel: n=9, T=7-9, N=77

Residuals :
   Min. 1st Qu.  Median 3rd Qu.    Max.
-2710.0  -679.0    63.3   633.0  4380.0

Coefficients :
                        Estimate Std. Error t-value Pr(>|t|)
eyeTrTRUE               -114.796    341.999 -0.3357  0.73713
qst_genderMale          -417.201    361.115 -1.1553  0.24796
qst_ethniDutch           983.280    497.199  1.9776  0.04797 *
qst_ethniOther            98.016    817.493  0.1199  0.90456
qst_ethniOther European  675.137    576.609  1.1709  0.24165
qst_ethniSouth American -186.840   1062.035 -0.1759  0.86035
qst_majorEconomics        13.753    374.320  0.0367  0.97069
qst_majorOther          -354.839    556.549 -0.6376  0.52375
qst_yrs2                 612.887    542.598  1.1295  0.25867
qst_yrs3                 263.359    575.973  0.4572  0.64750
qst_yrs4+                539.307    491.198  1.0979  0.27223
qst_expYes              -539.634    582.195 -0.9269  0.35398
qst_tradYes              671.235    398.435  1.6847  0.09205 .
```

```
---
Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1

Total Sum of Squares:    119310000
Residual Sum of Squares: 95368000
F-statistic: 1.06203 on 13 and 55 DF, p-value: 0.40987
>
> subjects$y = subjects$numTrades

Oneway (individual) effect Within Model

Call:
plm(formula = fm, data = curData, model = "within", index = c("Session",
    "Subject"))

Unbalanced Panel: n=9, T=7-9, N=77

Residuals :
   Min. 1st Qu.  Median 3rd Qu.    Max.
 -97.60  -21.20   -3.92   17.10  205.00

Coefficients :
                         Estimate Std. Error t-value Pr(>|t|)
eyeTrTRUE                -6.28071   12.54645 -0.5006  0.61666
qst_genderMale            5.63275   13.24775  0.4252  0.67070
qst_ethniDutch           29.60845   18.24009  1.6233  0.10453
qst_ethniOther          -13.53260   29.99027 -0.4512  0.65182
qst_ethniOther European   8.54054   21.15328  0.4037  0.68640
qst_ethniSouth American  29.52053   38.96147  0.7577  0.44864
qst_majorEconomics       -0.28363   13.73219 -0.0207  0.98352
qst_majorOther            1.38550   20.41738  0.0679  0.94590
qst_yrs2                -31.93532   19.90556 -1.6043  0.10864
qst_yrs3                -36.41568   21.12997 -1.7234  0.08481 .
qst_yrs4+               -44.56323   18.01993 -2.4730  0.01340 *
qst_expYes              -18.16222   21.35820 -0.8504  0.39512
qst_tradYes             -16.21959   14.61686 -1.1096  0.26715
---
Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

```
Total Sum of Squares:    168930
Residual Sum of Squares: 128350
F-statistic: 1.33772 on 13 and 55 DF, p-value: 0.22041
>
> subjects$y = subjects$numOffers
Oneway (individual) effect Within Model

Call:
plm(formula = fm, data = curData, model = "within", index = c("Session",
    "Subject"))

Unbalanced Panel: n=9, T=7-9, N=77

Residuals :
   Min. 1st Qu.  Median 3rd Qu.    Max.
-119.00  -32.40   -3.17   24.60  221.00

Coefficients :
                         Estimate Std. Error t-value Pr(>|t|)
eyeTrTRUE                -8.35734   16.18221 -0.5165  0.60554
qst_genderMale           12.51123   17.08673  0.7322  0.46403
qst_ethniDutch           42.50720   23.52577  1.8068  0.07079 .
qst_ethniOther          -26.85173   38.68096 -0.6942  0.48757
qst_ethniOther European  18.90398   27.28315  0.6929  0.48838
qst_ethniSouth American  37.03183   50.25186  0.7369  0.46117
qst_majorEconomics      -11.12995   17.71155 -0.6284  0.52974
qst_majorOther            0.73823   26.33401  0.0280  0.97764
qst_yrs2                -26.30993   25.67386 -1.0248  0.30547
qst_yrs3                -38.38069   27.25309 -1.4083  0.15904
qst_yrs4+               -44.21637   23.24181 -1.9024  0.05711 .
qst_expYes              -32.00830   27.54746 -1.1619  0.24526
qst_tradYes             -14.51886   18.85259 -0.7701  0.44123
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    277230
Residual Sum of Squares: 213510
```

```
F-statistic: 1.26246 on 13 and 55 DF, p-value: 0.26360
>
> subjects$y = subjects$avgStock
Oneway (individual) effect Within Model

Call:
plm(formula = fm, data = curData, model = "within", index = c("Session",
    "Subject"))

Unbalanced Panel: n=9, T=7-9, N=77

Residuals :
   Min. 1st Qu.  Median 3rd Qu.    Max.
 -6.000  -1.800  -0.506   0.976  14.000

Coefficients :
                         Estimate Std. Error t-value Pr(>|t|)
eyeTrTRUE                0.055083   0.909797  0.0605   0.9517
qst_genderMale           0.855953   0.960652  0.8910   0.3729
qst_ethniDutch          -0.156972   1.322668 -0.1187   0.9055
qst_ethniOther          -0.194352   2.174724 -0.0894   0.9288
qst_ethniOther European  2.109785   1.533915  1.3754   0.1690
qst_ethniSouth American  2.256488   2.825264  0.7987   0.4245
qst_majorEconomics      -0.021113   0.995780 -0.0212   0.9831
qst_majorOther           1.303988   1.480553  0.8807   0.3785
qst_yrs2                -0.548683   1.443438 -0.3801   0.7039
qst_yrs3                 0.917282   1.532225  0.5987   0.5494
qst_yrs4+                0.293509   1.306703  0.2246   0.8223
qst_expYes               0.591204   1.548775  0.3817   0.7027
qst_tradYes              0.081110   1.059932  0.0765   0.9390

Total Sum of Squares:    746.1
Residual Sum of Squares: 674.9
F-statistic: 0.446318 on 13 and 55 DF, p-value: 0.94425
>
> subjects$y = subjects$avgMoney
Oneway (individual) effect Within Model
```

```
Call:
plm(formula = fm, data = curData, model = "within", index = c("Session",
    "Subject"))

Unbalanced Panel: n=9, T=7-9, N=77

Residuals :
   Min. 1st Qu.  Median 3rd Qu.    Max.
-1550.0  -455.0   -35.6   443.0  2850.0

Coefficients :
                        Estimate Std. Error t-value Pr(>|t|)
eyeTrTRUE                -70.652    223.758 -0.3158  0.75219
qst_genderMale          -330.474    236.266 -1.3987  0.16189
qst_ethniDutch           423.762    325.301  1.3027  0.19269
qst_ethniOther          -223.053    534.858 -0.4170  0.67666
qst_ethniOther European  167.595    377.256  0.4442  0.65686
qst_ethniSouth American -609.163    694.854 -0.8767  0.38066
qst_majorEconomics       -89.111    244.905 -0.3639  0.71596
qst_majorOther          -637.928    364.132 -1.7519  0.07979 .
qst_yrs2                 445.951    355.004  1.2562  0.20905
qst_yrs3                  98.620    376.840  0.2617  0.79355
qst_yrs4+                400.058    321.375  1.2448  0.21319
qst_expYes              -444.144    380.911 -1.1660  0.24361
qst_tradYes              236.453    260.683  0.9071  0.36438
---
Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1

Total Sum of Squares:    49516000
Residual Sum of Squares: 40824000
F-statistic: 0.900866 on 13 and 55 DF, p-value: 0.55737
```

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Samenvatting (Dutch summary)

Markten vervullen ten minste drie belangrijke functies in de economie. Ten eerste, markten staan handel toe. Goederen en diensten kunnen worden herverdeeld naar diegenen die hen het hoogst waarderen. Ten tweede, markten zorgen er voor dat risico's worden samengevoegd en worden verminderd. Een degelijke diversificatie vermindert de hoeveelheid risico die individuen lopen. Ten derde, markten kunnen informatie aggregeren. Het is deze derde functie van markten die het onderwerp vormt van dit proefschrift.

Door hun transactieprijzen hebben markten het potentieel om diverse informatie te aggregeren en om signalen af te geven aan agenten over relatieve, *fundamentele*, waarde van verschillende goederen en diensten. De taak van het evalueren van relatieve waardes van de hoeveelheid goederen geproduceerd door de maatschappij lijkt een immense taak, toch zorgen competitieve markten (tenminste in de theorie) voor een oplossing voor dit probleem, in een onbedoelde vorm van "crowd-sourcing". Dit proces wordt *prijsontdekking* genoemd. Relatief hoge prijzen, bijvoorbeeld, verzenden een signaal dat een bepaald goed erg waardevol is voor een maatschappij – agenten hebben dan een prikkel om het aanbod (de productie) van dat goed te verhogen, terwijl op hetzelfde moment de vraag naar het goed afneemt (als consumptie en/of als input voor productie). Op deze manier kunnen prijzen fungeren als maatschappelijke gids die vertelt hoe te consumeren en hoe productieve hulpbronnen te verdelen. Als prijsontdekking heeft plaatsgevonden, wordt gezegd dat markten *efficiënt* zijn.

Echter, het probleem is dat er geen garantie is dat markt prijzen precies alle individuele preferenties *zullen* aggregeren, op die manier dat de relatieve prijzen correct de fundamentele waarde reflecteren. Sterker nog, er is geen garantie dat relatieve prijzen bij benadering alle individuele preferenties aggregeren. Als prijzen verschillen van de fundamentele waardes, wordt gezegd dat er sprake is van misprijzing op de markt. Een patroon waarin prijzen kunnen afwijken van de fundamentele waardes is een *luchtbel*. In goederenmarkten is een luchtbel een periode van continue groeiende overprijzing, beëindigd door middel van een scherpe daling, of *crash* van prijzen richting de fundamentele waarde. Als fundamentele waares relatief stabiel zijn gedurende deze periode, dan groeien prijzen tot een dag waarop ze spectaculair ineenstorten.

Deze evenementen zorgen vaak voor chaos in hun kielzog. Degenen die zich onbewust zijn van een crash, ervaren significante verliezen die vaak leiden tot effecten in andere delen van de economie. De directe kosten van een luchtbel worden gevormd door de overinvesteringen die het gevolg zijn van de tijdelijke overprijzing van een goed. De indirecte kosten van een luchtbel zijn de gevolgen van de kenmerkend grote en snelle herdistributie van vermogen dat zich voordoet als prijzen ineenstorten aan het einde van een luchtbel. Deze grote fluctuaties in vermogen kunnen leiden tot sociale onrust en kunnen overvloeien naar de rest van de economie.

Dit proefschrift bestaat uit drie experimentele studies die verschillende aspecten van een luchtbel bekijken. Hoofdstuk 3 laat zien dat het tijdspad dat fundamentele waardes volgen de efficiëntie van markten beïnvloedt. De notie dat fundamentele waardes prijzen beïnvloeden wordt over het algemeen als waar aangenomen, maar het vernieuwende aan dit hoofdstuk is dat het laat zien dat omkeerpunten in fundamentele waardes ook efficiëntie kunnen beïnvloeden. Het hoofdstuk laat zien dat markten efficiënter presteren gedurende een neerwaartse gang van fundamentele waardes dan in het geval van een opwaartse gang. De implicaties van deze asymmetrie is dat het misschien nodig is dat beleid ook asymmetrisch is.

Hoofdstuk 4 bestudeert de creatie en destructie van financiële aandelen van bedrijven door middel van het gebruik van aandeeluitgiften en het heraankopen van aandelen. De resultaten laten zien dat het heraankopen van aandelen zorgt voor een toename van de prijs van het goed, en dat een aandeel uitgifte zorgt voor een afname van de prijs van het goed, vergeleken met een scenario waarin geen interventie plaats vindt. Deze effecten zijn consistent met de kapitaalstructuurpuzzle, een negatieve correlatie die kenmerkend is voor de prijs en het aanbod van aandelen. Ten tweede, het empirische patroon dat wordt geobserveerd is consistent met een model van drie handelaars typen – fundamental, speculator en momentum – die een wisselwerking hebben in de markt. Tot slot, de neerwaartse druk op prijzen als gevolg van aandeeluitgiften drijven de prijzen naar beneden in de richting van, maar niet tot aan, de fundamentele waardes. Deze neerwaartse wrijving op de fundamentele waarde komt door de impact van een interventie op het deel van de totale voorraad aan eenheden en geld die door ieder handelaarstype wordt vastgehouden.

Hoofdstuk 5 is een studie naar het gebruik van informatie in een luchtbelmarkt en de relatie tot navolgend keuzegedrag. Gebruik makend van technieken die oogbewegingen volgen, wordt een experiment uitgevoerd die ingaat op hoe individuen die handelen op een markt zich focussen op het scherm waar het experiment op wordt uitgevoerd. Ten opzichte van overwegingen omtrent het experimenteel ontwerp, is er bewijs dat slechts enkele typen van dividendinformatie de prijsontdekking beïnvloeden. Om de data van de oogpatronen te verklaren, wordt het verkrijgen van informatie als stabiel bevonden over een verscheidenheid aan socio-demografische maatstaven. Het laatste stuk van de analyse gebruikt de data van de oogpatronen om korte termijn gedrag van individuen en markten te voorspellen. Aandacht voor ontvangen dividenden speelt een prominente rol, zowel in termen van toekomstige prijs toenames, als in termen van individuele handelspatronen. Markt crashes worden voorgegaan door een sterke daling in aandacht voor koopkansen, terwijl wanneer een crash onderweg is, aandacht neigt terug te keren naar het aankoopgedeelte van een scherm. De recente convulsies in het globale economische systeem hebben laten zien dat er sterke zorgen zijn ten aanzien van de mogelijkheid van het marktsysteem om "de zaken voor elkaar te hebben". Dit proefschrift is een kleine stap voorwaarts in de richting van het beter begrijpen van dat systeem en het verbeteren van de prestaties.